Assessment of the variability and uncertainty of soil organic carbon inventories in heterogeneous arid and alpine environments

Dissertation
Zur Erlangung des akademischen Grades

Inauguraldissertation
Zur Erlangung der Würde eines Doktors der Philosophie
vorgelegt der
Philosophisch-Naturwissenschaftlichen Fakultät der
Universität Basel

Ulrike Hoffmann (geb. Poppe)
aus Wiesbaden (Deutschland)

Basel, 2012

Genehmigt durch die Philosophisch-Naturwissenschaftliche Fakultät auf Antrag von

Prof. Dr. Nikolaus Kuhn
(Universität Basel)
Fakultätsverantwortlicher / Dissertationsleiter

Prof. Dr. Stephan Glatzel
(Universität Rostock)
Korreferent

Basel, den 26. Juni 2012
Prof. Dr. Martin Spiess
Dekan

Abstract

Surface soils, forming the largest pool of terrestrial organic carbon, may be able to sequester atmospheric carbon and thus mitigate climate change. So far the soil organic carbon (SOC) literature is dominated by studies in humid, agricultural environments and limited attention has been given to arid and mountain ecosystems that are highly sensitive to environmental change. Thus, our knowledge on the feedbacks between spatial patterns of SOC stocks and temporally and spatially changing environmental conditions (such as land use and climate) in these ecosystems remains insufficient. Analyzing these feedbacks is a major challenge due to the large spatial variability that is caused by the high activity of geomorphic processes in arid and mountain ecosystems.

Due to the increasing interest in reliable estimates of SOC stocks in various environments, this thesis intends to improve our understanding of the linkages between environmental variability and the uncertainty of SOC stock assessments in dynamic geomorphic systems. These uncertainty estimates are expected to contribute to the development of an efficient sampling design with guidelines for the compilation of SOC inventories in heterogeneous environments.

This PhD focuses on three case studies, i) Sede Boquer in the arid Northern Negev desert (Israel), ii) the Kananaskis country in the Canadian Rocky Mountains and iii) the area between the Kleine Scheidegg and Grindelwald in the Swiss Alps. Each study site is characterized by a high geomorphic activity. Based on SOC stocks, which were established for each study site, the main objective of this thesis is to determine the uncertainty associated with SOC assessments that are mainly linked i) to the high spatial variability of the soil forming factors and soil properties, ii) to analytical errors during the measurements of the soil properties, and iii) to uncertainties that arise from the spatial interpolation of local point data with different local spatial interpolation techniques.

The first case study aimed to identify the relationship between surface characteristics, vegetation coverage, SOC concentration and stocks in the arid northern Negev in Israel. To identify controlling factors of SOC stocks on rocky desert slopes, we compared soil properties, vegetation coverage, SOC concentration and stocks between ecohydrological units. The results show a large spatial variability of SOC, soil bulk density and soil thickness which is mainly attributed to the disconnectivity of overland flows and the local deposition of fine sediments. The calculated SOC stocks indicate that rocky desert slopes represent a significant amount of SOC of soil-covered areas of 1,54 kg C m^2, with an average SOC stock over the entire study area of 0.58 kg C m^2. The spatial variability within the study site is dependent on differences in eco-climate, microtopography, surface processes, soil formation and properties, and vegetation. These differences were mapped within the study site in terms of ecohydrological units, which provide an effective tool to detect spatial patterns and thus to reduce uncertainties of SOC stocks in arid environments. Furthermore, the results indicate that microscale water supply and NPP are the limiting conditions for the

formation of SOC in arid, rocky deserts and thus suggest a high sensitivity to potential climate changes. Even though SOC stocks are smaller than in more humid environments, it is of major importance for the functioning and thus conservation of arid ecosystem.

Mountain environments are heterogeneous and dynamic geomorphic environments that are highly sensitive to land use and climate change. Local geomorphic processes, which are driven by strong topographic gradients, cause a large heterogeneity of the parent material that represent a major challenge in the assessment of SOC stocks in mountain environments.

The first mountain case study is located in the Front Range of the Canadian Rocky Mountains, which is characterized by a very low human impact and a natural boreal forest cover. The second mountain case study, located between the Kleine Scheidegg and Grindelwald (Swiss Alps), is characterized by a long history of agricultural land use. Uncertainties in SOC stocks due to analytical errors and spatial variability of SOC stocks are assessed using a nested sampling design in combination with Gaussian error propagation and Taylor series expansion along several transects that are equally spaced in each study site. Additionally, in Grindelwald the ability of different spatial interpolation methods to cope with data of high spatial variability was tested.

SOC stocks for the upper 30 cm of the mineral soil in Kananaskis and Grindelwald ranged from 3.01 to 24.94 kg C m^{-2} (with a mean of 6.40 kg C m^{-2}) and from 2.52 to 23.46 kg C m^{-2} (mean = 8.93 kg C m^{-2}), respectively. Both studies confirm that multiple regression analysis and ANOVA explain only parts of the SOC variability and that the largest uncertainty is introduced through the large variability of the coarse fraction. Therefore, mountain geomorphic processes, which dominantly control the grain size of the parent material, are responsible for the large uncertainty of SOC stocks in mountain environments. It is thus argued that detailed geomorphological maps, which represent the grains size of the parent material, have a high potential to reduce the uncertainty that is associated with the coarse fraction. Additionally, both studies confirm that stratified nested sampling designs, as applied in this study, are helpful to discriminate the sources of uncertainty and to identify the relevant scales of spatial variability.

Based on the results of the three case studies, general guidelines were derived for the compilation of SOC stocks in arid and alpine environments. These guidelines have a strong focus on the assessment on the quantity and quality of SOC stocks in geomorphic active ecosystems.

Zusammenfassung

Der Boden als die bedeutendste, nicht vermehrbare Georessource der Zukunft ist eine wichtige Komponente im globalen Kohlenstoffkreislauf. Die Anforderungen an die Ressource Boden werden sich durch den globalen Landnutzungs- und Klimawandel stark verändern. Insbesondere in klimasensitiven ariden und alpinen Regionen werden erhebliche Veränderungen des Bodenkohlenstoffs erwartet. Diese Veränderungen ergeben sich einerseits aus den veränderten externen Faktoren, andererseits durch Anpassung der geomorphologischen Dynamik, die wiederum die bodenbildenden Faktoren modifiziert. Die Bestimmung von Boden-Kohlenstoffinventaren in diesen Regionen ist aufgrund der großen Heterogenität ihrer naturräumlichen Ausstattung mit erheblichen Unsicherheiten verbunden. Die Analyse dieser Unsicherheiten und die Ableitung der methodischen Konsequenzen ist wesentlicher Bestandteil dieser Dissertation.

In drei Feldstudien wurden Kohlenstoffinventare für komplexe, dynamische Landschaftssysteme in ariden und alpinen Ökosystemen berechnet. Zu den drei Feldstudien zählen ein Tal in der Nähe von Sede Boquer in der nördlichen Negev Wüste (Israel), ein Transekt entlang des Highway 40 in Kananaskis Country in den Kanadischen Rocky Mountains und die Fläche zwischen Grindelwald und der Kleinen Scheidegg in den Schweizer Alpen. In diesen Gebieten wurden geostatistische Ansätze zum Beprobungsdesign und der räumlichen Vorhersage in landschaftsökologisch vergleichbar wenig erforschten Gebieten untersucht. Besonderer Fokus lag auf der Fehleranalyse und der Identifikation der Fehlerquellen zur Bestimmung der Bodeneigenschaften und der Kohlenstoffinventare. Maßgeblicher Faktor der Heterogenität der naturräumlichen Ausstattung in allen drei Gebieten ist die geomorphologische Aktivität, die erheblich zur kleinräumigen Variabilität der Korngrößen in den Untersuchungsgebieten beiträgt.

Die als „Rocky Desert“ klassifizierte Landschaft der Negev-Wüste wies in den bodenbedeckten Bereichen eine durchschnittliche Bodenbedeckung von 18 cm auf mit einem durchschnittlichen SOC stock von 1,54 kg C m^2. Die Ergebnisse dieser Feldstudie belegen eine hohe Variabilität des Boden-Kohlenstoffs die im Wesentlichen auf Unterschiede der solaren Einstrahlung, der Bodenfeuchte und der Vegetationsdichte zurückzuführen sind. Dabei werden die beiden letzten Parameter v.a. von den durch die geomorphologischen Prozesse bestimmten Bodeneigenschaften stark beeinflusst. Es konnte ferner gezeigt werden, dass die Kartierung öko-hydrologischer Einheiten, welche die variablen Bodeneigenschaften widerspiegeln, eine Extrapolation von SOC Inventaren in ariden Gebieten möglich ist.

Die Studien in den alpinen Untersuchungsgebieten belegen, dass Regressionsansätze mit einzelnen Umweltfaktoren als auch multiple Regressionsansätze für die Kohlenstoff-variabilität dieser Landschaftsräume nur einen unzureichenden Erklärungsanteil liefern. Durch die Anwendung multihierarchischer Beprobungsdesigns in Kombination mit Fehleranalysen (Gauss`sche und Taylor Fehlerfortpflanzung) wurde der analytische Fehler, als auch die räumliche Variabilität des Kohlenstoffinventars als eine Funktion der

Kohlenstoffkonzentration, der Lagerungsdichte des Bodens, der Grobfraktion und der Bodentiefe berechnet. Die Fehleranalysen zeigen, dass die Grobfraktion und die Kohlenstoffkonzentration des Bodens die höchsten räumlichen Fehler aufweisen, während mit der Lagerungsdichte die höchste analytische Ungenauigkeit verbunden ist. Um die Unsicherheiten, die aus der räumlichen Variabilität der Bodeneigenschaften von Kohlenstoffinventaren alpiner Untersuchungsgebiete folgen, möglichst gering zu halten, sollte die Beprobung der Grobfraktion und der Kohlenstoffkonzentration mit besonders hoher räumlicher Auflösung analysiert werden. Hierzu werden detaillierte geomorphologische Kartierungen empfohlen.

Zusammenfassend konnte gezeigt werden, dass alle Untersuchungsgebiete durch eine hohe räumliche Variabilität der Bodeneigenschaften gekennzeichnet sind, für die einfache Erklärungszusammenhänge nicht ausreichen. Bei der Konzeption des Beprobungsdesigns, der Probendichte und der Auswahl des Interpolationsverfahrens muss die hohe räumliche Variabilität besondere Berücksichtigung finden. Hierarchische Beprobungsdesigns, wie sie in dieser Arbeit angewendet wurden, haben ein hohes Potential die Unsicherheiten, die aus der räumlichen Variabilität folgen, zu analysieren. Ohne die Verwendung von hochaufgelösten Umweltdaten, wie beispielsweise geomorphologische Karten, mit denen Informationen der Korngrössenverteilung des Bodens abgebildet werden, ist die Genauigkeit eines SOC Inventars in komplexen, dynamischen Landschaftssystemen stark limitiert.

Contents

LIST OF FIGURES 9

LIST OF TABLES 10

1. INTRODUCTION 1

2. STATE OF THE ART OF SOC INVENTORIES 5

2.1 Significance of soils in the global carbon budget 5

2.2 SOC in geomorphic dynamic areas and selection of study sites 7

2.2.1 Dryland ecosystems 8

2.2.2 Mountain ecosystems 8

2.2.3 Agricultural activity and mountain ecosystems 10

2.3 Calculation of SOC stocks 11

2.4 Scales and controls of SOC variability 12

2.5 Benefits and limitations of SOC inventories 14

3. SOIL ORGANIC CARBON IN THE ROCKY DESERT OF NORTHERN NEGEV (ISRAEL) 17

3.1 Introduction 17

3.1.1 Soil organic carbon and the global carbon cycle 17

3.1.2 Carbon stocks in drylands 17

3.1.3 SOC-stock calculation and links to soil-forming factors 19

3.1.4 Estimation of dryland SOC stocks 19

3.2 Study Site 20

3.3 Methods 22

3.3.1 Ecohydrologic units along rocky desert slopes at Sede Boker 22

3.3.2 Soil sampling and data analysis 22

3.3.3 Laboratory and statistical SOC analysis 23

3.4 Results 25

3.4.1 Variability of SOC stocks and controlling soil properties 25

3.4.2 SOC stocks, soil properties and ecohydrology 25

3.5 Discussion 26

3.5.1 SOC stocks, surface characteristics and vegetation 26

3.5.2 Surface processes and SOC stocks 29

3.5.3 SOC stock comparison with other drylands 29

4. ASSESSMENT OF VARIABILITY AND UNCERTAINTY OF SOIL ORGANIC CARBON IN A MOUNTAINOUS BOREAL FOREST (CANADIAN ROCKY MOUNTAINS, ALBERTA) 33

Abstract 34

4.1 Introduction 34

4.2 Study site 36

4.3 Material and Methods 38

4.3.1 Sampling strategy 38

4.3.2 Soil sampling 39

4.3.3 Soil analyses 40

4.3.4 Calculation of SOC stocks 40

4.3.5 Evaluation of uncertainties 41

4.4 Results 43

4.4.1 Spatial variability of soil properties 43

4.4.2 Relation between soil properties and site characteristics 46

4.4.3 Analytical error and effects of spatial uncertainties on a SOC inventory 48

4.5 Discussion 49

4.5.1 SOC stocks in mountain soils 49
4.5.2 Relation of SOC-related soil properties to environmental conditions 51
4.5.3 Sources of uncertainty of soil organic carbon stocks 51
4.5.4 Implications for regional SOC inventories 53
4.6 Conclusion 55
5. SPATIAL VARIABILITY OF SOIL ORGANIC CARBON STOCKS IN AN ALPINE SETTING (GRINDELWALD, SWITZERLAND) 57
Abstract 58
5.1 Introduction 58
5.2 Study site 60
5.3 Materials and methods 61
5.3.1 Sampling strategy 61
5.3.2 Soil analyses 64
5.3.3 Calculation of SOC stock 64
5.3.4 Spatial variability 64
5.3.5 Evaluation of uncertainties 65
5.3.6 Spatial interpolation and prediction of the target variable 67
5.4 Results 68
5.4.1 Spatial variability and controls of SOC stocks 68
5.4.2 Analytical error and effects of spatial uncertainties on SOC inventory 70
5.4.3 Spatial interpolation and regional SOC inventory 71
5.5 Discussion 75
5.5.1 Controls of SOC stocks in mountain environments 75
5.5.2 Interpolation and utility of regional datasets 75
5.5.3 Sources and effects of uncertainty of soil organic carbon stock calculation 76
5.6 Conclusion and implications for the compilation of mountain SOC inventories 77
6. SYNTHESIS 79
6.1 SOC stocks in arid and mountain environments 79
6.2 Discussion of the guiding research questions 83
7. GUIDELINES TO COMPILE SOC INVENTORIES IN DYNAMIC GEOMORPHIC SYSTEMS 87
8. OUTLOOK 91
ACKNOWLEDGEMENTS 107

List of Figures

Figure 1.1: Concept of spatial variability of soil forming factors and soil properties and uncertainties of calculated SOC inventories. 2

Figure 2.1: The Carbon Cycle for the 1990's – pools and fluxes (IPCC, 2007). 5

Figure 2.2: Conceptual and mathematical framework for SOC stock calculation. 6

Figure 3.1: Location of the study site and sampling points. 21

Figure 3.2: Geological cross section with lithological formations of the study site. 21

Figure 3.3: SOC concentration, vegetation coverage and soil depth against aspect. 26

Figure 3.4: SOC concentration, vegetation coverage and soil depth against ecohydrologic unit and aspect. 27

Figure 3.5: SOC concentration as a function of depth below surface, plotted for every sample. 28

Figure 3.6: Scatterplot of SOC concentration and $SOC_{stock,ehu}$ of sampled soils versus vegetation coverage and soil depth. 28

Figure 4.1: Location, topography, and terrain inventory of Kananaskis basin and sampling points within the study area. 36

Figure 4.2: Distribution (normal values and log-transformed values) and qq-plots of *SOC*, *CF*, *BD* and SOC_{stock}. 44

Figure 4.3: Boxplot representing the minimum, first, second (median) and third quantile and maximum of the SOC concentration, coarse fraction), bulk density, SOC stock of the mineral soil and of the organic horizon in each transect (T01 to T17). 45

Figure 4.4: Boxplots concerning the relationship between log(*SOC*), *CF*, *BD*, log(SOC_{stock}), log(*OHC*) and soil properties as well as soil forming factors. 46

Figure 4.5: Distribution of coarse fraction stratified based on the lithology and the geomorphic environment. 54

Figure 5.1: Location of the Grindelwald area within the Swiss Alps and elevation with shaded relief and location of the sampling points within the study site. 60

Figure 5.2: Land-cover, geology and soil type in the study site. 62

Figure 5.3: Distribution and quantile-quantile plots of *SOC*, *CF*, *BD* and SOC_{stock}. 69

Figure 5.4: SOC stocks as a function of elevation, plan curvature, profile curvature and slope. 70

Figure 5.5: Maps of the interpolated results for the entire study site. 72

Figure 5.6: Cross validation of interpolated and observed SOC stocks based on inverse distance, ordinary kriging, block kriging with block size of 250 m and 500 m, and regression kriging. 73

Figure 5.7: Relationship of RMSE and sampling size of different interpolation methods. 74

List of Tables

Table 3.1: Observed and mapped properties of the ecohydrologic units in the study area. 23

Table 3.2: Mean soil depth, median soil and vegetation coverage and minimum, median, mean, max, and standard deviation of SOC stocks with respect to aspect and ecohydrologic units. 24

Table 3.3: Minima, median, mean, maxima, and standard deviation of measured soil properties relevant for the calculation of the SOC stock. 26

Table 3.4: Global comparison of SOC and SOC stocks in different arid environments. 29

Table 4.1: Site characteristics of sampled transects (T01-T17). 39

Table 4.2: Mean and standard deviation (STD) of the measured and calculated soil properties up to 30 cm depth for each studied transect T01-T17. 43

Table 4.3: Analytical errors and spatial uncertainties of the studied soil properties given as the coefficient of variation. 48

Table 4.4: Global comparison of SOC stocks in different mountain environments. 50

Table 5.1: Abbreviations (as used in Figure 5.4), number of samples and short description of each class of the categorical datasets (geology, soil type, grain-size index and land use). 63

Table 5.2: Minimum, mean, median, maximum, standard deviation (STD) and CV of the measured and calculated soil properties up to 30 cm depth for the entire dataset (n = 403). 68

Table 5.3: R^2, F-statistic and p-values of ANOVA concerning the relationship between SOC0.25 and site characteristics. 69

Table 5.4: Analytical errors and spatial uncertainties of the studied soil properties given as the coefficient of variation. 70

Table 5.5: Summary statistics of interpolated $SOC_{stock,30cm}$ using different interpolation methods. 71

Table 5.6: Comparison of interpolation efficiency for the considered soil properties. 74

Table 6.1: Summary and main conclusions of the three case studies. 81

1. Introduction

Soils store almost twice as much carbon (C) as the atmosphere and therefore play a key role in the global carbon cycle (Amundson, 2001; Kutsch et al., 2009). Consequently, small changes in the soil organic carbon (SOC) pool, which represent the most active C pool in the soil, can have large implications for atmospheric CO_2-concentrations (Smith, 2004b). The risk of global warming and the potential to use soils as a carbon sink in the context of the Kyoto Protocol have increased the attention of the scientific community to SOC stocks and fluxes in terrestrial ecosystems (Houghton, 2007). However, the size and dynamics of SOC stocks, particularly in dynamic geomorphic systems, which are sensitive to climate changes, are still insufficiently constrained. Precise measurements and estimates of the spatial distribution of SOC stocks are necessary to quantify the SOC sink or source capacity of soils in changing environments. The spatial variation of SOC is significantly influenced by environmental factors such as climate (Djukic et al., 2010; Jobbágy and Jackson, 2000), topography (Egli et al., 2009; Garcia-Pausas et al., 2007), soil and bedrock materials (Leifeld et al., 2005; Tan et al., 2004), vegetation (Luyssaert et al., 2008; Zhou et al., 2006), and disturbances due to surface processes (Berhe et al., 2008; Yoo et al., 2006) and human activity (Bell, 2009; Morgan et al., 2010).

Soil organic carbon inventories of larger spatial scales, as required by the Kyoto Protocol, generally suffer from the large spatial variability of the environmental factors and the soil properties that control SOC stocks (Figure 1.1). Major uncertainties of SOC studies are thus related to the large spatial variability associated with the soil forming factors and the soil properties and the limited sampling densities due to the time-consuming soil sampling. Thus, interpolation techniques used to interpolate spatial point data to larger areas are only partially capable to represent the variability of SOC stocks. This is especially true for arid and mountain environments that are characterized by a high geomorphic activity that introduces a large variability of the parent material. Due to the major challenges that are associated with the high variability, SOC stocks in arid and mountain environments are generally not well represented and require more detailed investigations.

Thus the following research question stimulated the present PhD-thesis:

1. Which soil property introduces the largest variability and thus the largest uncertainty in the calculation of SOC stocks?
2. How do regional environmental data present the spatial variability of the SOC stock and contribute to the compilation of regional SOC stocks?
3. What are the major implications to improve regional SOC inventories?

Guided by these questions, this thesis intends to improve our understanding of the linkages between environmental variability and the uncertainty of SOC stock assessments in dynamic geomorphic systems at different spatial scales. These uncertainty estimates are expected to contribute to the development of an efficient sampling design and to an estimation and interpolation of regional SOC stocks with high accuracy.

The **main objective of this thesis** is to determine the uncertainty associated with SOC assessments that are mainly linked i) to the high spatial variability of the soil forming factors and the relevant soil properties, ii) to analytical errors during the measurements of the soil properties, and iii) to uncertainties that arise from the spatial interpolation of local point data with different local spatial interpolation techniques (Figure 1.1).

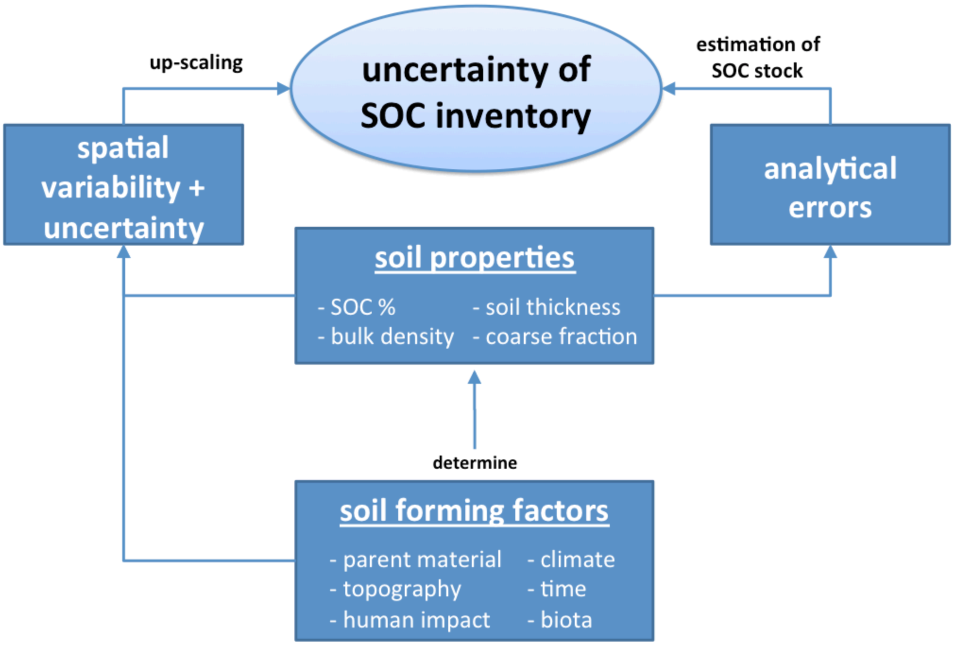


Figure 1.1: Concept of spatial variability of soil forming factors and soil properties and uncertainties of calculated SOC inventories.

Due to the increasing interest in reliable estimates of SOC stocks in various environments, the major focus is to quantify the uncertainties involved in the entire process of SOC stock assessments in different ecosystems and at different scales. Therefore, this PhD focuses on three field studies that are characterized by a high geomorphic activity. In contrast to a multitude of SOC studies that intend to identify the driving mechanisms of SOC stocks in small scale and/or homogenous areas, the PhD considers the characteristic heterogeneity of arid and mountain environments and intends to provide guidelines towards the compilation and uncertainty estimates of SOC inventories in dynamic geomorphic systems.

The first study site is located in the Negev Desert and is representative for an arid ecosystem where detailed SOC inventories focusing on the influence of different environmental factors are still missing. The second and third study sites are situated in mountain environments. One is located in the Front Range of the Canadian Rocky Mountains, which is characterized by a negligible human impact and a natural forest cover, while the other is located below the Eiger North Wall (Grindelwald, Switzerland), which has a long history of agricultural land use.

The contents of the present PhD-thesis is structured as followed: Chapter 2 provides an overview on the current state of knowledge of SOC assessments. Chapters 3-5 were written as stand-alone manuscripts for publication in peer-reviewed journals. In chapter 3 the field study conducted in the Negev Desert (Israel) is presented. The major aim was to quantify the relationship between surface characteristics and vegetation coverage and spatial patterns of SOC concentrations and SOC stocks in the arid northern Negev. A stratified sampling scheme based on ecohydrological units was employed to calculate SOC stocks. To identify controlling factors of SOC stocks on rocky desert slopes, we compared soil properties, vegetation coverage, SOC concentration and stocks between the ecohydrological units.

In chapter 4, we present results from the boreal forest ecosystem in the Canadian Rocky Mountains. Uncertainties in SOC stocks due to analytical errors and spatial variability of SOC stocks are assessed using Gaussian error propagation and Taylor series expansion along transects. The nested sampling design allowed identifying the major sources of uncertainty in a natural mountain environment.

Chapter 5 of the thesis presents and discusses results from a field study in Grindelwald, Swiss Alps. This study compares different spatial interpolation methods to map the SOC stocks in this alpine environment and evaluates the effects of the sampling density on the root mean square error of interpolated maps.

Finally, chapter 6 synthesizes and concludes the findings of the three studies and provides guidelines for the assessment of SOC stocks in dynamic geomorphic environments and an outlook for further research.

2. State of the art of SOC inventories

2.1 Significance of soils in the global carbon budget

Soils store about 1500 Gt organic carbon in the top one meter of the Earth surface and a further 900 Gt between 1–2m (Schlesinger et al., 2000; Stutter et al., 2009). Consequently, the soil organic carbon (SOC) represents 55 % of the terrestrial carbon storage and is twice as large as the atmospheric carbon pool, in which ~600 Gt C is stored (Amundson, 2001). Despite the SOC storage being much smaller than the carbon store in the oceans (36.000 Gt C) and the lithosphere (66-100 x 10^6 Gt C), SOC is much more sensitive to environmental changes due to the short residence times and its reactive, labile character (Batjes, 1996). Consequently, soils represent one of the most dynamic components of the global carbon cycle (Figure 2.1) and have a central position in the global climate system (Houghton, 2007; Wigley and Schimel, 2005). This implies that small changes in SOC-content could significantly increase, or mitigate current atmospheric CO_2 increase. For instance, a change of global SOC pool by just 10 % equals the entire anthropogenic CO_2 emitted over the last 30 years (IPCC, 2007; Kirschbaum, 2000).

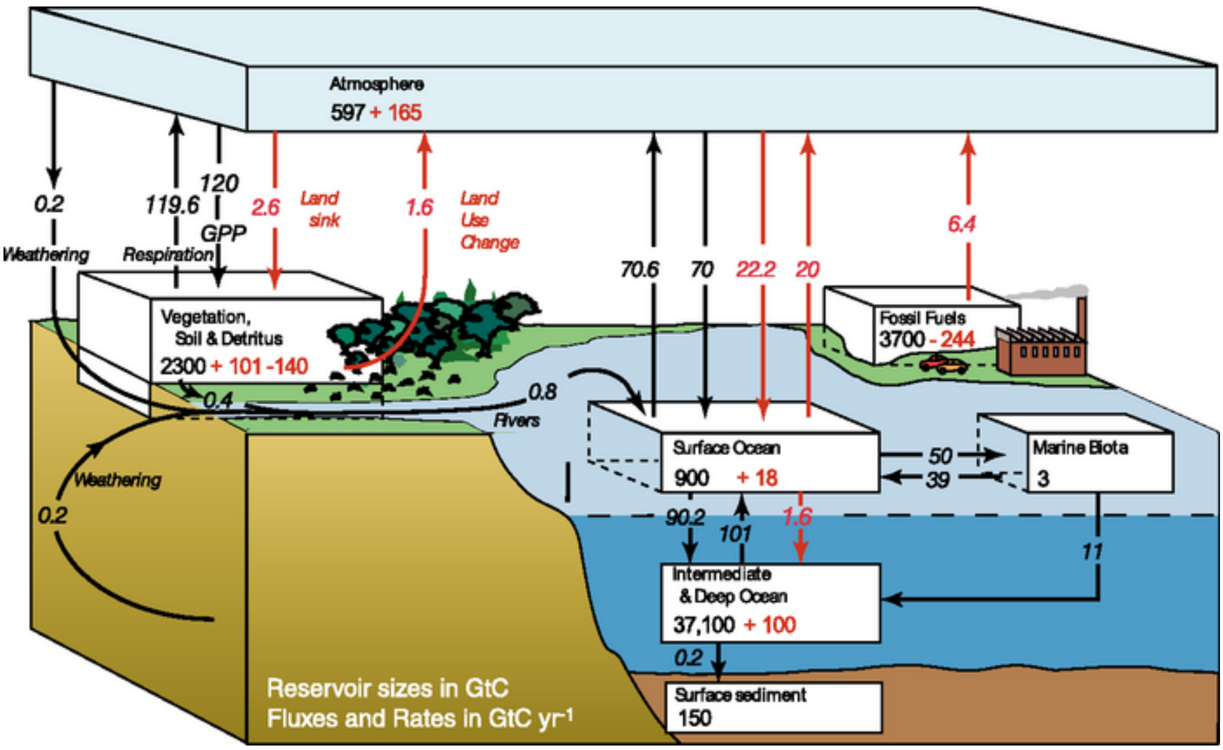


Figure 2.1: The Carbon Cycle for the 1990's – pools (black numbers) and fluxes (red numbers) are given in Gt and Gt yr^{-1}, respectively (IPCC, 2007).

According to the UN Framework convention on Climate change (IPCC, 2007), which suggests nations to tackle their CO_2 budgets and to decrease CO_2 emissions to the atmosphere, the impact of soils on the global carbon cycle has gained increasing public and scientific interest during the last 10 years. Global and regional SOC stocks will be heavily affected by the anticipated changes in atmospheric CO_2 and the predicted rise in global air temperatures (Schimel et al., 2000). More prominent threats are posed to global soils by human impacts such as deforestation, biomass burning, land use change and environmental pollution (Batjes, 1996). Within the UN Framework convention on climate change, the focus of climate change mitigation has been put on carbon pools that sequester and release CO_2 within a human timeframe. Consequently, an increasing understanding of spatial patterns and dynamics of SOC stocks and their contribution to regional, national and global carbon cycles is required (IPCC, 2007).

Due to differences in soil, climate and agricultural management, SOC stock assessment should be calculated at regional level supported by regional environmental data (Homann et al., 1995; Kutsch et al., 2009 ; Mishra, 2009). Thus, regional SOC stock assessments provide an important framework to study the patterns and dynamics of organic carbon in soils and support the development and implementation of climate policies (Goidts and van Wesemael, 2007; Meersmans et al., 2008).

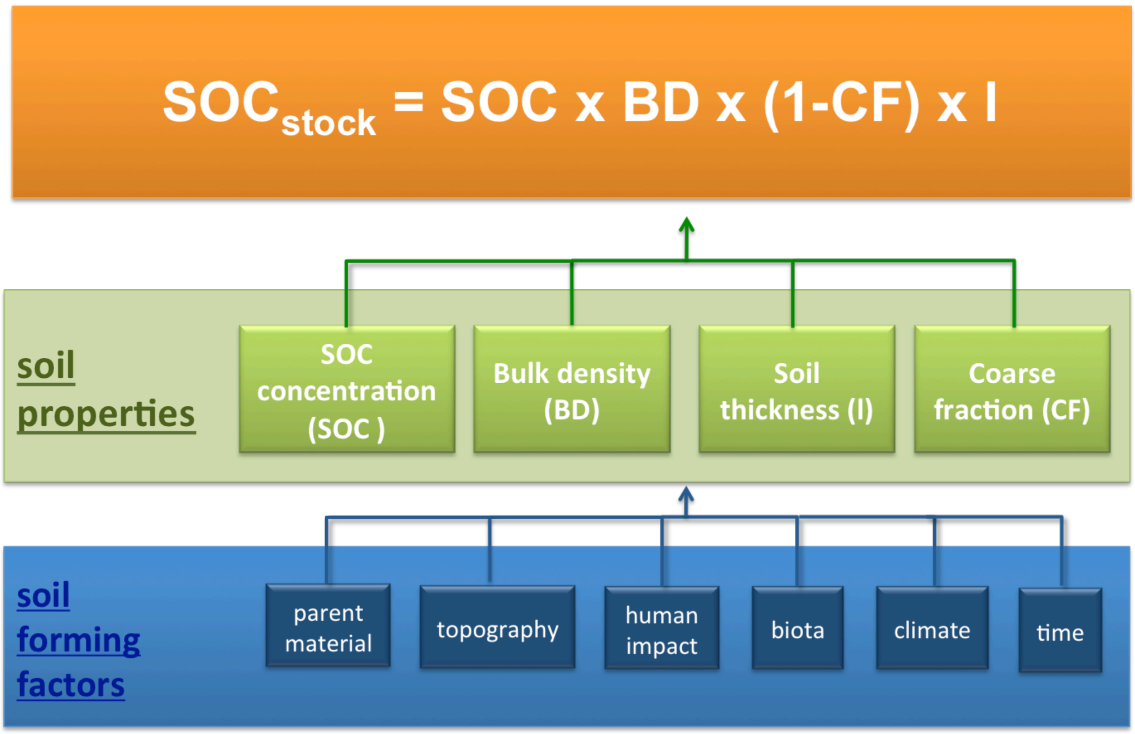


Figure 2.2: Conceptual and mathematical framework for SOC stock calculation.

The mixing of air and water in the atmosphere and within the oceans results in relatively minor spatial variability of atmospheric CO_2 and CO_2 dissolved in ocean water. In contrast, due to limited mixing, SOC concentrations in soils may change within a short distance (e.g. a few centimeters or meters) from very low (<0.1 %) to very high (>70 %). This is especially true for arid and mountain ecosystems that are characterized by a high variability of the soil forming factors (e.g. time, parent material, topography, climate, vegetation and organisms, site management/land use), which in turn affect the formation and degradation of organic carbon in soils (Figure 2.2). A high degree of variability in these environments is introduced to the high activity of geomorphic processes that control the large variability of soil forming parent material (Lieb et al., 2011). In arid environments, the patchiness of surface runoff processes and sediment transport causes a large variability of soil thicknesses and soil moisture availability (Burke et al., 1999; Schlesinger, 1990). In contrast, strong topographic gradients in mountain environments cause the variation of soil properties (e.g. grain size) due to local geomorphic processes (Haeberli et al., 2007; Meehl et al., 2007; Schröter et al., 2005).

Even though arid and mountain ecosystems are considered very sensitive to environmental changes (e.g. climate change and human impacts), our knowledge on the spatial patterns and dynamics of SOC is insufficient. Our limited knowledge on the contribution of arid and mountain environments to the global SOC storage and their response to global change mainly results from the small number of SOC stocks and the major challenges and uncertainties that are associated with the assessment of SOC stocks in these environments. The improvement of these stocks requires a more explicit consideration of the coupling between geomorphic processes and SOC stock variability.

2.2 SOC in geomorphic dynamic areas and selection of study sites

Soils are considered to be highly sensitive to climate change (IPCC, 2007). However, neither climate change nor the associated response of SOC is globally uniform. Global warming is likely to increase both, CO_2 assimilation by vegetation (net primary production) and CO_2 release by ecosystem respiration. The net effect of soils in a warming atmosphere depends on the relative sensitivity of decomposition and net primary production. The direction of this net effect is strongly disputed. Based on a review of changing rates of primary production and decomposition, Kirschbaum (2000) concludes that warming will likely have the effect of reducing SOC by stimulating decomposition rates more than primary production. Budge et al. (2011), in contrast, suggest that it remains uncertain whether the net feedback effect of SOM will be positive or negative in response to rising temperatures. This uncertainty exacerbates the need to establish accurate regional predictions of SOC response in climate change “hot spots” with different environmental conditions as demanded by the Kyoto protocol. Dryland ecosystems and mountain environments are generally considered as major “hot spots” in which strong climate changes are expected (IPCC, 2007).

Therefore, a short description of the particular conditions and processes of these environments with respect to SOC stocks will be given below.

2.2.1 Dryland ecosystems

Arid ecosystems are especially vulnerable to environmental change. Hence, they exhibit large and rapid responses to even small changes of climate conditions and comprise an important but mainly unexplored role in the global carbon discourse (Lal et al., 2011; Yair, 1990). Arid environments are characterized by a patchy plant cover and a heterogeneous distribution of SOC, which is mostly concentrated beneath shrubs (Burke et al., 1999; Schlesinger, 1990; Schlesinger, 1995). Soil formation in these areas is limited by water availability and the intensity of soil and wind erosion processes. Furthermore, soils in drylands are prone to degradation and desertification owing to human activities. Consequently, the majority of dryland soils can be considered far from SOC saturation, suggesting a high potential of SOC uptake (Farage et al., 2003; Lal, 2003). Even though drylands occupy 47.2 % of the earth´s land surface, their importance in the global carbon cycle was recently underestimated (FAO, 2004). For example, results from Rotenberg and Yakir (2010) show that dryland forests in Israel take up carbon at rates similar to forests in more humid continental Europe. Based on these results, they suggest that 1 Pg out of 3.2 Pg generating the annual increase in atmospheric concentration of CO_2 can be sequestered by reforestation in drylands. In contrast to soils from humid regions, dryland soils are less likely to loose SOC because the lack of water limits SOC mineralization, and the flux of SOC into the atmosphere. Thus, the residence time of SOC in desert soils can be much longer than in humid region soils (Glenn et al., 1993). As a consequence, the ratio of the soil to living biomass SOC stock is greater in drylands than tropical forests, (Farage et al., 2003; Lal, 2009; Lal et al., 2011), suggesting large increases of SOC with reforestation of the areas, as supposed by (Rotenberg and Yakir, 2010). However, there is little data available on dryland soils and our knowlegde of the interaction between environmental factors and SOC stocks in dryland ecosystems remain insufficient. Therefore, detailed SOC inventories in dryland ecosystems focusing on the small-scale variability and the influence of different environmental factors are highly needed.

Based on these considerations, Sede Boquer in the Northern Negev desert was chosen as a representative study site of arid environments (Olsvig-Whittaker et al., 1983; Yair, 1994; Yair and Danin, 1980). The study site represents a small tributary catchment (4.5 ha), in which SOC stocks were studied along a cross-section covering slopes of different topographic expositions and specific climatic conditions (for more details see chapter 3).

2.2.2 Mountain ecosystems

High mountain systems, such as the alpine and subalpine regions, are strongly affected by global warming (Haeberli et al., 2007; Schröter et al., 2005; Theurillat and Guisan, 2001). Furthermore, mountain SOC stocks and -dynamics are likely to be influenced more strongly by accelerated greenhouse effect than those of temperate and tropical biomes (Meehl et al., 2007).

Geomorphic systems in alpine ecosystems respond sensitively to climate changes due to the high geodiversity. Furthermore, climatic changes are not evenly distributed. The mean temperature of the European Alps increased twice as much as the global average since the late 19th century and precipitation as well as other hydrometeorological variables show significant regional and seasonal difference in trend (Lieb et al., 2011). The fate of the SOC storage and turnover in that scenario is largely unknown (Körner, 2003).

The observed atmospheric warming directly impacts the extent of glaciers and the distribution of permafrost (mass, geometry, melt runoff) in the mountains. Further effects are changing hydrological conditions in the mountain drainage basins, and a generation of considerable amounts of sediment available for transport and disposition in high-elevations with considerable contents of SOC (Slaymaker et al., 2009). Other processes that are connected indirectly to changes of the atmosphere, such as floods, debris flows and landslides may react time-delayed to changes of the hydro-climate and sediment supply and thus may have a large potential to exchange and store SOC.

Alpine soils are expected to contain large amounts of SOC, which may become a further source of atmospheric carbon dioxide as a result of global warming. Alpine soils cover roughly 4×10^6 km^2 worldwide (Körner, 2003), but despite the large extent research information on these soils and understanding about the SOC stocks and influence of environmental factors on SOC stock and turnover is limited. Such information is needed to improve predictions and models of the possible response of SOM to warming (Zhen et al., 2007).

Owing to their importance, a better understanding of the processes that affect SOC storage in alpine soils is needed. Estimations of SOC stocks in mountain ecosystems, however, are complicated by their heterogeneous nature. Strong topographic gradients do not only affect the soil forming factors, but also lead to strong gradients of soil properties that are relevant for SOC stock in mountain terrain. At the regional scales, elevation and thus temperature differences are identified as the dominant controls on mountain SOC (Bolstad and Vose, 2001; Djukic et al., 2010; Van Miegroet et al., 2007). In contrast, factors such as slope, aspect, pH, clay-content, stand age, microtopography, and landscape position may dominate the SOC variability at the local scale. Small-scale, local variability may even impose strong scatter at large-scales and conceal relationships between SOC and topography.

Failing to understand and incorporate this interplay of controlling factors on different spatial and temporal scales inhibits predictions of the response of SOC in mountain soils to global warming. Thus, the Kananaskis Country (Canadian Rocky Mountains) was chosen as a study site, which is characterized by mountain topography and a limited human impact. In this case study, major focus was given on the site scale variability of SOC stocks that are dominantly driven by a natural geomorphic process regime. Therefore, 17 transects (each

36 m long) were sampled along a topographic gradient (from 1400 m to 2300 m above sea level) following the Highway 40 for approx. roughly 50 km. In each transect, the variability of each soil property in equation 2.1 (see page 11) was calculated and their contribution to the uncertainty of SOC stocks was assessed.

2.2.3 Agricultural activity and mountain ecosystems

Accurate regional SOC stocks under agricultural impact are necessary to meet the requirements of the Kyoto Protocol. Following this political guideline, there has been an increasing interest to establish SOC stocks in agricultural ecosystems on different spatial scales. In countries where the agricultural sector is the primary control of the total SOC stocks, there are several regional studies about the total SOC content and its spatial variability. For instance (Krogh et al., 2003) stated that nearly 40 % of the total SOC stocks in Denmark are present in the plough layer, implying that agricultural operations, land use and environmental change affect a considerable amount of carbon.

Agricultural soils are prone to degradation and erosion in particular in rugged terrain. The global compilation presented by Stallard (1998) has motivated the interest of lateral carbon fluxes induced by soil erosion and its contribution to the global carbon cycle. Quinton et al. (2010) estimates the impact of agricultural soil erosion on biogeochemical cycles. They state that sediment flux due to water erosion is about 28 Pg yr^{-1} and that further 7 Pg yr^{-1} of sediment are mobilized by tillage and wind erosion, leading to a total sediment flux of about 35 ± 10 Pg yr^{-1}. This corresponds to an agricultural carbon erosion flux of 0.5 ± 0.15 Pg C that is delivered to river systems by water erosion each year. To understand the effect of erosion on the SOC stock different experiments (Berhe, 2006; Kuhn et al., 2009; Quine and Oost, 2007) indicate that sediment mobilization could result in a significant increase in the rate of SOC mineralization. This could lead to the loss of over 20 % of the total SOC as carbon dioxide. However, recent observations (e.g. Schlünz and Schneider, 2000; Yoo et al., 2005) suggest that SOC losses from soil that is re-deposited after a short transport phase are relatively low (< 2.5 % of eroded SOC), and therefore not very significant for the global SOC budget. On the other hand, a large amount of SOC that is delivered to rivers will be mineralized within the river system in a short period of time (Aufdenkampe et al., 2011; Mayorga, 2005).

In addition to the disruption of soil structure during erosion and the subsequent release of carbon dioxide, enhanced emissions over longer time frames are associated with a reduction in the capacity of eroded soils to support plant growth resulting in lower carbon inputs through plant and root matter.

In contrast to increased mineralization, erosion could also foster carbon sequestration (Berhe et al., 2008; Stallard, 1998; Van Oost, 2007). Erosion leads to the mixing of carbon-poor subsoil in the plough layer, and if the newly exposed mineral soil surfaces bind organic matter, SOC stocks may increase. Long-term effects of carbon sequestration are associated with carbon storage and decreased decomposition in sedimentary sinks at hillslopes and within the fluvial system (Hoffmann et al., 2009).

In contrast to the global trend, the conversion of alpine forest to agricultural landscapes resulted in increasing SOC stocks. In Switzerland for instance, around 540 000 ha agricultural areas are located in the Swiss Jura mountains and in the Alps and are used as meadows and pastures with 80 % extensively grazed areas, and the residue traditionally being used for hay. Grazing in these areas affected the amount of soil carbon concentration (Bolliger et al., 2008). Grazing increased SOC content relative to light grazing and haying (Leifeld and Fuhrer, 2009; Seeber, 2005). A higher SOC content in the topsoil of grazed compared with non-grazed grasslands has been shown for other climatic regions before (Franzluebbers et al., 2000), and soil incorporation of plant materials has been suggested as one possible mechanism (Manley et al., 1995; Schuman et al., 2001). Also in hayed mountainous grasslands, management intensity (i.e. cutting frequency and fertilization) affects the SOC although no univocal relationship between management intensity and SOC storage could be shown so far (Zeller et al., 2000; Zeller et al., 1997).

The imbalance between carbon and nutrient fluxes and erosion are of primary importance for agricultural landscapes and crucial for our understanding how erosion threatens the sustainability of food production and human welfare in many parts of the world. Even though, erosion rates in mountain ecosystems are in the same of magnitude of agricultural landscape (Montgomery, 2007), little is known on the coupling between topography, land use and sediment-burden carbon fluxes in mountains.

To further investigate the impact of land use in mountain ecosystems, the Grindelwald area was chosen as a study site in a heterogeneous mountain environment in the Swiss Alps, which is strongly modified by human land use since several hundred years. In this case study, we investigate the spatial variability of soil properties and SOC stocks along several 30 m long transects in a changing mountain environment. Additionally, regional datasets and different interpolation techniques were used to analyze the quality of regional dataset for the assessment of regional scaled SOC inventories.

2.3 Calculation of SOC stocks

The term **SOC stock** refers to the amount of soil organic carbon stored within the soil of a given area beneath the land surface (generally given in kg m^{-2})[1]. Consequently, SOC stocks are a function of the depth averaged total organic carbon content *SOC* (mass of carbon per unit mass of soil; g g^{-1}), the bulk density *BD* [kg m^{-3}] of the soil (including the soil's fine and

[1] In contrast to SOC stock, the term **SOC pool** refers to the functioning of the soils in the global carbon cycle, while the term **SOC inventory** is associated with the spatially distributed SOC stock in a certain area.

the coarse fraction), the fraction of stones CF [$g\ g^{-1}$] larger than 2mm (e.g. coarse fraction) and the soil depth l [m] (Rodeghiero et al., 2009):

$$SOC_{stock} = SOC \times BD \times (1-CF) \times l \qquad \text{(equation 2.1)}$$

Each of these soil properties are variable in time and space and are determined by complex interaction of soil forming factors such as climate, parent material, vegetation and time (Allen et al., 2010). While qualitative relationships between soil forming factors and soil carbon are generally known, there are large uncertainties regarding specific, quantitative relationships on different spatial scales between the soil forming factors and relevant soil properties. Quantitative relationships are required for accurate SOC stocks, since soil properties are mostly unknown at larger scales and SOC properties are derived based on their relationship with the environmental conditions (e.g. soil forming factors such as land use, geology, climate, geomorphology and topography), which are in turn derived from datasets at regional or even global scales. Thus the accuracy of SOC inventories is dependent on the relation of the relevant soil properties to the environmental conditions and the accuracy and resolution of the regional datasets that represent these environmental conditions. Thus inaccurate SOC stocks generally results from i) unknown quantitative relationships between soil properties and soil forming variables and ii) the limited resolution of the available regional datasets. The latter generally results from the spatial scale discrepancy between soil forming processes, which operate at very small scale (e.g. pedon scale) and the scale of the available data.

To conclude, the following research questions remain:

i) How well do regional datasets represent the small-scale variability of soil properties that are used to calculate SOC stocks? and

ii) How large are the uncertainties associated with a limited relation between environmental regional dataset and the relevant soil properties?

These research questions are associated to the three guiding questions of this PhD that are formulated in chapter one. These research questions are studied through the analysis of the site-scale variability of the relevant soil properties and their relation to available regional datasets that represent the soil forming factors.

2.4 Scales and controls of SOC variability

Soil forming processes and soil properties vary at spatial scales that range from soil aggregates to continents (Lark, 2005). In general, three scales of soil forming processes and their relation to environmental conditions have been described:

First, the **plant/pedon scale** is associated with spatial patterns of SOC ranging up to 200 m. Dominant controls are vegetation patterns and plant community dynamics (Garcia-Pausas et al., 2007; Moni et al., 2010). Plant material provides the main source of SOC through litter drop, the production of root exudates and root mortality. Consequently the size, morphology (tree, shrub, grass) and spatial distribution of plants affect the areas where SOC is input and stored.

Second, at the **community scale**, which ranges between 20 m and a few kilometers, spatial variability of SOC is dominated by soil type and site management (Allen et al., 2010). Soil type influences SOC due to the effect that soil nutrition can have on biomass production; higher nutrition levels are generally observed in soil types with high contents of fine soil particles (e.g. silt and clay). Several studies have revealed a good correlation between clay contents and SOC stocks (Brady and Weil, 2002; Burke et al., 1995; Don et al., 2007; Leifeld et al., 2005; Singh et al., 2011), because they provide both, physical and chemical mechanisms to protect SOC from microbial decomposition. At the upper end of this scale (few km²) land management presents a further control on the spatial variability of SOC. In grazing lands, the application of fertilizers increases not only the yield but also SOC, particularly where soil has inherently low soil fertility (Schnabel et al., 2001). Additionally, the activity of grazing animals (grassing, dropping of dung, cattle erosion) will also influence the spatial variability of SOC (Bisigato et al., 2008).

Third, at scales larger than a few square kilometers, e.g. the **regional or landscape scale**, climate and topography are dominating SOC variability (Dai and Huang, 2006; Ganuza, 2003; Wang et al., 2010). Temperature and rainfall effects both plant biomass production and soil respiration. With increasing temperatures, both plant biomass production and soil respiration rates tend to increase (Dalal and Chan, 2001). However, all else being equal, soil carbon generally increases from warmer to cooler and from drier to wetter locations (Amundson, 2001). Up to a certain soil moisture, biomass production and decomposition rates increase at approximately the same rate. However, excessively high soil moisture contents will lead to anaerobic conditions within the soil and a decrease in decomposition rates, thus increasing SOC storage (Schlesinger, 1995; Yang et al., 2008).

Topography will affect the spatial variability of soil organic carbon at all three scales due to several effects. First, topography modifies soil moisture and thus exerts an indirect control on SOC variability (Liechty et al., 1997; Prichard et al., 2000; Stutter et al., 2009). Second, slope and curvature are major topographic parameters that control fluxes of water, sediment, and other nutrients and hence modifies soil formation, soil depth, moisture and hence biomass production and C input (Egli et al., 2009; Homann et al., 1995; Perruchoud et al., 2000). Thin soil depths generally characterize steeper slopes and thus lower SOC stocks, while higher soil moisture, and hence biomass production, contributes to higher SOC concentrations and -stocks in downslope positions (Berhe et al., 2008; Schwanghart and Jarmer, 2011; Yoo et al., 2006). At the largest scale, topography modifies temperature and precipitation and thus exerts a control of climate parameters that effect SOC formation and decomposition.

To conclude, the scale considerations indicate that topography, which drives geomorphic processes, varies at all spatial scales and thus exert a dominant and insufficiently considered control of SOC stocks. However, our knowledge between the link of soil organic carbon and geomorphic processes remains insufficient at all scales.

2.5 Benefits and limitations of SOC inventories

Studies of soil organic carbon have contributed to our understanding of its role and feedbacks in the global carbon cycle and within the climate system (Kirschbaum, 2000; Perruchoud et al., 2000; Post and Kwon, 2000).

Considerable progress in carbon accounting has been made worldwide during the last 15 years. The benefit of SOC studies are fourfold: (1) they establish the relation of SOC stocks to environmental conditions such as elevation and temperature (Bolstad and Vose, 2001; Brady and Weil, 2002; Djukic et al., 2010; Garcia-Pausas et al., 2007; Leifeld et al., 2005; Perruchoud et al., 1999; Tan et al., 2004) aspect and slope position (Egli et al., 2009; Garcia-Pausas et al., 2007; Homann et al., 1995; Lal, 2005b; Perruchoud et al., 2000), soil, bedrock material and sediment texture (Banfield et al., 2002; Brady and Weil, 2002; Hoffmann et al., 2009; Lal, 2005b; Leifeld et al., 2009; Tan et al., 2004), pH (Djukic et al., 2010; Falloon and Smith, 2009; Heckman et al., 2009), topography (Berhe et al., 2008; Liechty et al., 1997; Prichard et al., 2000; Yoo et al., 2006), vegetation and forest stand age (Homann et al., 1995; Luyssaert et al., 2008; Pregitzer and Euskirchen, 2004; Zhou et al., 2006) and disturbance due to human activity (Czimczik et al., 2005; Morgan et al., 2010; Wang et al., 2008) (compare Table A.1 in appendix A), (2) they examine the amount and residence times of soil organic carbon content under various environmental conditions and (3) they predict changes of SOC stocks under different scenarios of climate change (Carter and Gregorich, 2006; Simbahan et al., 2006; Spielvogel et al., 2009) and land use change (Don et al., 2011; Guo and Gifford, 2002; Poeplau et al., 2011) and (4) give recommendations for management and policy purposes (e.g. carbon trading) (Bell, 2009; Houghton, 1995; Houghton, 2007).

Traditionally, SOC stocks have been obtained i) for small homogenous study sites (few km² in size) in which only one relevant environmental variable (e.g. temperature, elevation) changes with time or in space, while the other environmental variables (e.g. land use and geology) remain constant (Bolstad and Vose, 2001; Djukic et al., 2010; Garcia-Pausas et al., 2007; Leifeld et al., 2005; Perruchoud et al., 1999; Sheikh et al., 2009; Tan et al., 2004), ii) for regional, low relief study sites, which are characterized by more or less homogenous land use and/or climate patterns (Genxu et al., 2002; Goidts and van Wesemael, 2007; Grüneberg et al., 2010; Hancock et al., 2010; Moorman et al., 2004; van Wesemael et al., 2010), iii) to analyze the impact of human induced soil erosion (Mabit et al., 2008; Pennock and van Kessel, 1997; Shukla and Lal, 2005) and iv) on a global scale, with strong restriction and simplified model assumptions regarding the spatial variability of the relevant soil properties (Amundson, 2001; Cox et al., 2000; Eliseev and Mokhov, 2007; Friedlingstein et al., 2006; Smith, 2004a; Xianli et al., 2010; Zeng et al., 2004).

All of these studies are based on simplifying assumptions regarding the underlying control mechanisms of environmental conditions on SOC stocks. At local scales, there has been a focus on relatively homogenous study sites where the effect of the variability of one controlling variable was studied (e.g. land use or elevation change). However, these studies do not represent the interaction of the controlling variables and are not representative for larger heterogonous areas. At the global scale, SOC stocks are based on simplified relations between environmental conditions and SOC storage (Cox et al., 2000; Jones et al., 2005). Global SOC studies thus do not represent the uncertainty associated with the smaller scale variability, which potentially might introduce large uncertainties of global SOC estimates.

In summary, systematic studies in heterogeneous areas with highly dynamic soil forming factors and strong interactions of the driving mechanisms, e.g. such as arid and mountain environments, are largely missing. However, arid and mountain ecosystems comprise a large fraction of the earth surface and are sensitive to environmental changes. Thus these ecosystems may have a strong impact on the global carbon cycle, which is currently not well constrained. As a consequence, there is a strong demand for further research to provide methods for the assessment of SOC stocks in these environments. In order to make predictions of changes in SOC stocks due to climate change and human impact, it is important to evaluate current regional soil C stocks for such “hot spots” of environmental change, with large, rapid, and variable responses to even the smallest changes. Their spatial heterogeneous characters, further demands to identify the spatial controls on SOC concentration which in turn improves the knowledge of processes which determine soil C storage and vice versa (Homann et al., 1995; Meersmans et al., 2008; Stutter et al., 2009).

To conclude, the PhD focuses on the variability of arid and mountain environments. Therefore, special attention was driven on study sites that represent the characteristic heterogeneity of these environments and did not focus and simplified (e.g. homogenous), small scale areas.

3. Soil organic carbon in the rocky desert of northern Negev (Israel)

This chapter has been published in Journal of Soils and Sediments as: Hoffmann, U., Yair, A., Hikel, H., Kuhn, N. J. (2012): Soil organic carbon in the rocky desert of northern Negev (Israel). Journal of Soils and Sediments, 12: 811-825.

J Soils Sediments (2012) 12:811–825
DOI 10.1007/s11368-012-0499-8

SOILS, SEC 1 • SOIL ORGANIC MATTER DYNAMICS AND NUTRIENT CYCLING • RESEARCH ARTICLE

Soil organic carbon in the rocky desert of northern Negev (Israel)

Ulrike Hoffmann · Aaron Yair · Harald Hikel · Nikolaus J. Kuhn

Received: 24 July 2011 / Accepted: 2 March 2012 / Published online: 5 April 2012

Abstract
Purpose So far, the soil organic carbon (SOC) literature is dominated by studies in the humid environments with huge stocks of vulnerable carbon. Limited attention has been given to dryland ecosystems despite being often considered to be highly sensitive to environmental change. Thus, there is insufficient research about the spatial patterns of SOC stocks and the interaction between soil depth, ecohydrology, geomorphic processes, and SOC stocks. This study aimed at identifying the relationship between surface characteristics, vegetation coverage, SOC, and SOC stocks in the arid northern Negev in Israel.
Materials and methods The study site Sede Boker is ideally suited because of well-researched but variable ecohydrology. For this purpose, we sampled five slope sections with different ecohydrologic characteristics (e.g., soil and vegetation) and calculate SOC stocks. To identify controlling factors of SOC stocks on rocky desert slopes, we compared soil properties, vegetation coverage, SOC concentration, and stocks between the five ecohydrologic units.
Results and discussion The results show that in Sede Boker, rocky desert slopes represent a significant SOC pool with a mean SOC stock of 0.58 kg C m^{-2} averaged over the entire study area. The spatial variability of the soil coverage represents a strong control on SOC stocks, which varies between zero in uncovered areas and 1.54 kg C m^{-2} on average in the soil-covered areas. Aspect-driven changes of solar radiation and thus of water availability are the dominant control of vegetation coverage and SOC stock in the study area.
Conclusions The data indicate that dryland soils contain a significant amount of SOC. The SOC varies between the ecohydrologic units, which reflect (1) aspect-driven differences, (2) microscale topography, (3) soil formation, and (4) vegetation coverage, which are of greatest importance for estimating SOC stocks in drylands.

Keywords Drylands · Ecohydrology · Rocky deserts · SOC stock · Soil organic carbon · Topography

Responsible editor: Zucong Cai

U. Hoffmann (✉) · H. Hikel · N. J. Kuhn
Department of Environmental Science,
Physical Geography and Environmental Change,
University of Basel,
Klingelbergstrasse 27,
4056 Basel, Switzerland
e-mail: ulrike.hoffmann@unibas.ch

A. Yair
Department of Geography, Hebrew University of Jerusalem,
Mount Scopus,
Jerusalem 91905, Israel

1 Introduction

1.1 Soil organic carbon and the global carbon cycle

The global soil system is the largest terrestrial reservoir of organic carbon, which stores approximately 2,400 Pg (Pg=10^{15} g) of soil organic carbon (SOC) in the top 2 m (Amundson 2001; Kirschbaum 2000). Soil and climate systems are closely coupled through the exchange of C between the atmosphere, biosphere, and pedosphere (Berhe et al. 2008). Therefore, there has been increasing international interest in the ability of soils to affect atmospheric concentrations of carbon dioxide (CO_2) (Houghton 2007; Mishra et al. 2009; Sarmiento and Gruber 2002; Schlesinger 1977, 1990; Wigley and Schimel 2005). The risk of global warming and the potential to use soils as a carbon sink in the context of the Kyoto Protocol have increased the attention of the scientific community to SOC stocks and fluxes in terrestrial ecosystems, especially in regions sensitive to climatic change (Branchu et al. 1993; IPCC 2007; Mishra et al. 2009; Smith and Heath 2002). However, the size and dynamics of the global SOC pool are still not well known (IPCC 2007; Quinton et al. 2010; Seip 2001). Precise measurements and estimates of the spatial distribution of SOC stocks are necessary to quantify the SOC sink or source capacity of soils in changing environments. The spatial variation of SOC is significantly influenced by environmental factors such as climate, topography, soil and bedrock materials, vegetation, disturbance, and surface processes due to human activity (Tan et al. 2004).

1.2 Carbon stocks in drylands

Even though drylands occupy 47.2 % of the earth's land surface, their importance in the global carbon cycle received limited attention (Asner et al. 2003; Schimel 2010). Global dryland soils contain 15.5 % of the world's total SOC to 1 m depth (IPCC 2007; Lal 2003; Lal et al. 2001; Schimel et al. 2000). This is about 40 times more than what was added during the 1990s into the atmosphere through anthropogenic activities, estimated at 6.3 Pg C year^{-1} (IPCC 2007; Lal 2003; Lal et al. 2001; Schimel et al. 1994, 2000). Dryland ecosystems are often regarded as “hot spots” of climate change, with large, rapid, and variable responses to even the smallest changes of climate conditions (Farage et al. 2003; Lal 2003; Yair 1990). Furthermore, dryland soils are prone to degradation and desertification due to human activities. Consequently, the majority of degraded dryland soils can be considered as far from SOC saturation, suggesting a high potential of SOC uptake (Farage et al. 2003; Lal 2003). Additionally, recent results (Rotenberg and Yakir 2010) show that dryland forests in Israel take up carbon at rates similar to forests in more humid continental Europe. Based on these results, they suggest that 1 Pg out of 3.2 Pg generating the annual increase in atmospheric concentration of CO_2 can be sequestered by reforestation of dryland soils. In contrast to soils from humid regions, dryland soil areas are less likely to lose SOC because the lack of water limits SOC mineralization and therefore the flux of SOC into the atmosphere. Consequently, the residence time of SOC in desert soils can be much longer than in soils of humid regions (Glenn et al. 1993), and the ratio of the soil to living biomass SOC pool might be greater in drylands than in tropical forests (Farage et al. 2003; Lal 2009; Lal et al. 2001).

1.3 SOC-stock calculation and links to soil-forming factors

SOC stocks (kg C m^{-2}) are generally calculated based on the mean soil organic carbon contents SOC_c (g 100 g^{-1}) of the fine soil fraction (<2 mm), the mean bulk density BD (in grams per cubic centimeter), the mean mass ratio of coarse soil fragments (>2 mm) CF_i (g 100 g^{-1}), and the soil thickness d_{soil} (centimeters):

$$SOC_{stock} = 0.1 \times d_{soil} \times BD \times SOC_c \times (1 - CF/100) \quad (1)$$

In humid environments, which are characterized by strong agricultural activity, human-controlled land cover generally exerts a strong variability on SOC concentration that in turn dominates the spatial variability of SOC stock (Goidts and van Wesemael 2007; Grieve 2001; Lal 2005; Leifeld et al. 2005; van Wesemael et al. 2010). In arid environments, however, the link between SOC stocks and soil-forming factors (such as climate, vegetation, and bedrock material) is much more complex than in humid agricultural landscapes. Significant diurnal temperature changes and the water deficit result in high physical and low chemical weathering rates (FAO 2004). The strong disintegration of rocks and the low chemical transformation therefore suggest a strong control of properties of the parent material (e.g., given by soil thickness, BD, and CF in Eq. (1)) on SOC stocks. Parent material in arid environments is often transported during severe soil erosion caused by extreme precipitation events (Yair 1990). Wash processes, however, are not continuous but disconnected, and sediment is generally transported only over short distances due to the disconnectivity of overland flows (Michaelides and Chappell 2009; Yair 1992). Thus soils, especially in arid environments, need to be “considered as mobile systems, which has major consequences for terrestrial biogeochemical cycles” (Quinton et al. 2010). Furthermore, arid environments lack a continuous vegetation coverage but are dominated by shrub vegetation that concentrates the biogeochemical activity in “islands of fertility” (Schlesinger and Pilmanis 1998; Schlesinger et al. 1996). Therefore, the shift from continuous grassland to patchy shrub vegetation with increasing aridity introduces a further element of complexity in the distribution of SOC stocks.

1.4 Estimation of dryland SOC stocks

Due to continuous runoff under humid conditions, SOC stocks are generally related to the surface morphology, which controls processes such as erosion and deposition and thus SOC fluxes and sequestration (Egli et al. 2009; Griffiths et al. 2009; Rosenbloom et al. 2006; Tan et al. 2004; Yoo et al. 2006). Topographic parameters, such as slope (Berhe et al. 2008; Tsui et al. 2004), curvature (Rosenbloom et al. 2006; Yoo et al. 2006), and relief position (Glatzel and Sommer 2005), have been shown to correlate with SOC stock under humid conditions. In contrast to humid environments with well-developed soils, arid environments with shallow soils are characterized by a lack of connectivity in runoff causing in turn an exceedingly high spatial variability of soil depth (Laity 2008; Parsons and Abrahams 2009; Yair 1990;

Yair and Danin 1980). Since runoff exerts a strong control over water availability, soil formation, and soil erosion and deposition, simple relationships of topographic parameters (such as slope, curvature, and wetness index) and soil properties and SOC stocks are not expected in arid environments.

Vegetation needs to be considered as a major factor controlling SOC stocks in arid environments (FAO 2004; Zhou et al. 2011). First, strong variations of soil moisture availability cause a patchy vegetation distribution, which in turn may exert a strong control on carbon stocks (Olsvig-Whittaker et al. 1983; Schlesinger et al. 1996). Second, in contrast to humid environments, which are characterized by high net primary production (NPP) and increased organic matter mineralization, dry environments have lower NPP, but also lower decomposition rates (Lal 2009; Schlesinger 1991). Third, while high temperatures favor high CO_2 efflux, low decomposition rates (due to water deficit) limit vegetation-driven carbon sequestration in hot arid climates (Fang and Moncrieff 2001; Farage et al. 2003; Qi et al. 2002) and thus may limit the impact of vegetation on SOC stocks. Thus, the link between soil moisture, vegetation coverage, and soil properties to SOC stocks and their relative importance for the spatial patterns of SOC stock in arid environments are much less clear than under humid conditions.

The spatial variability of relevant soil properties (Eq. (1)) presents a major challenge to the establishment of SOC stocks in arid and semi-arid environments. Despite the apparent significance of the dryland SOC pool, systematic studies on the spatial variability and the effects of environmental factors (such as soil moisture and vegetation coverage) in rocky desert soils are still missing. Thus, there is a strong need to estimate SOC stocks in arid soils and to evaluate their importance under a changing climate (Rotenberg and Yakir 2010; Schimel 2010). This need provides the major motivation of our study, which aims (1) to determine SOC stocks in a range of ecohydrologically different slope environments, (2) to identify soil properties relevant for the SOC stocks in each ecohydrologic setting, and (3) to assess the effects of NPP (represented by vegetation coverage) on SOC stocks.

The study was conducted in the northern highlands of the Negev desert in Israel near the town of Sede Boker, which is ideally suited because of well-researched ecohydrology. The influence of surface properties and patches of rock and soil on ecohydrology and vegetation has been intensely investigated in this area (e.g., Evenari et al. 1980; Olsvig-Whittaker et al. 1983; Yair 1990; Yair and Danin 1980). Based on this research, it was possible to determine SOC stocks in a range of ecohydrologically different slope environments and to identify soil properties relevant for SOC concentration and stock. The established link between vegetation coverage and water supply at Sede Boker also offers the opportunity to test the effects of ecohydrology on SOC, especially the balance between NPP (indicated by vegetation coverage) and SOC-stock development.

2 Study site

The Sede Boker research area is located in a second-order drainage basin (4.5 ha) about 40 km south of Beersheva (30° 52′ N, 34°48′ E) in the northern Negev Desert of Israel (Fig. 1). The elevation ranges between 485 and 535 m above sea level. The mean annual air temperature in Sede Boker is 20 °C (Dan et al. 1972), and mean monthly temperatures vary from 9 °C in January to 25 °C in August. The average annual rainfall, observed during a 30-year period (Yair 1994), ranges from 34 to 167 mm, with an average of 91 mm (Kuhn and Yair 2004). Rainfall is concentrated during the winter season between October and April. Potential evaporation rates are approximately 2,500 mm, generating an arid climate (Evenari et al. 1980; Olsvig-Whittaker et al. 1983; Yair and Danin 1980).

The Upper Cretaceous bedrock stratigraphy is composed of three limestone formations that are the Netser, Shivta, and Drorim formation (Fig. 2). Based on Yair and Danin (1980), Olsvig-Whittaker et al. (1983), and Schreiber et al. (1995), the formations can be classified in four meso-scale surface structural units (Upper Netser, Lower Netser/Upper Shivta, Lower Shivta, colluvium above Drorim). The upper part of the slope is characterized by the Upper Netser formation with thinly bedded limestones and flint concretions. The lower part of the Netser and the Upper Shivta formation is a thinly bedded and densely fissured formation and could be considered as one structural unit according to Olsvig-Whittaker et al. (1983). The Lower Shivta formation is a massive unit with a low density of deep cracks. The Drorim formation represents the lowest unit, which is densely jointed and covered with an extensive colluvial mantle (Yair and Shachak 1982) (see Fig. 2). These bedrock formations provide distinctive surface properties influencing hydrology, plant communities, and therefore potentially the spatial distribution of SOC concentration and SOC stock.

In situ chemical weathering of bedrock is of minor importance for soil formation. Most of the substrate is not derived from the local limestone, but composed of aeolian loess-like sediments, which were deposited since the early Quaternary (Bruins 1986; Reifenberg 1947; Yaalon and Dan 1974). Based on the World Reference Base for Soil Resources (IUSS Working Group WRB 2006), the soil is dominantly classified as a desert brown Lithosol (Arkin and Braun 1965; Dan et al. 1972) with patchy and thin soil cover. Generally, the study area is characterized by three soil bedding types: (1) soil patches, which are mainly located at the base of rock steps, (2) soil material filling crevices

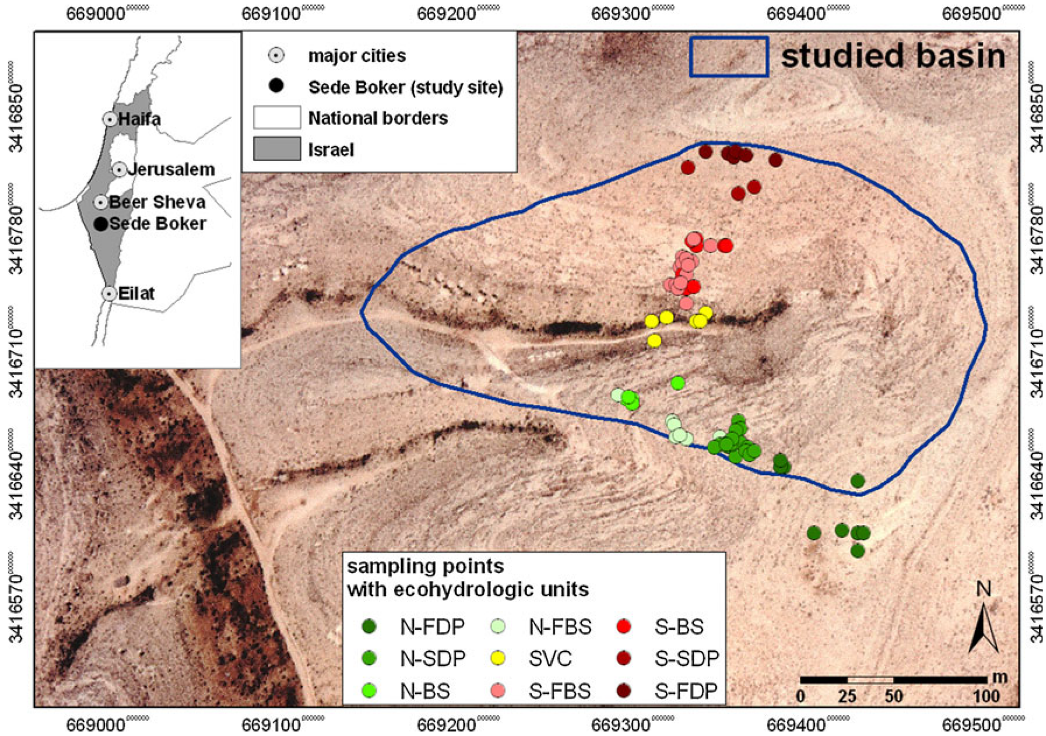


Fig. 1 Location of the study site and sampling points with respect to aspect and ecohydrologic units. *N* and *S* indicated northern and southern aspects, respectively. *FDP* flat desert pavement, *SDP* gently sloped desert pavement, *FBS* stepped and fissured bedrock slope, *BS* non-fissured bedrock slope, *SVC* slope and valley colluvium. Coordinates are given by projection system UTM longitude zone 36, latitude zone R, ellipsoid WGS 84

and fissures generated by rock shattering, and (3) colluvial soil sheets on bedding planes of the near surface rock strata. The loessic substrate is high in sand and silt (85–95 %), while clay content varies between 14.5 % in joints and crevices and 7–10 % in soil patches covering bedding planes (Olsvig-Whittaker et al. 1983; Yair and Danin 1980). Due to the arid conditions, with low vegetation coverage and high wind speeds and surface runoff, the soil genesis is

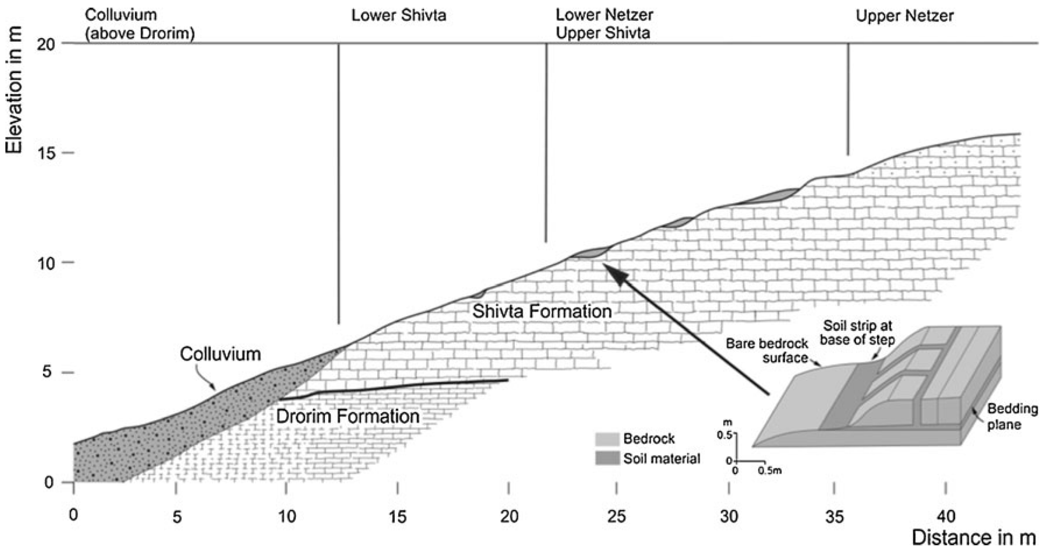


Fig. 2 Geological cross section with lithological formations of the study site modified after Olsvig-Whittaker et al. (1983)

strongly controlled by the erosion and deposition caused by wind and surface runoff (Olsvig-Whittaker et al. 1983).

Despite the meteorologic aridity, the vegetation of this region is considered to be at the transition of the Irano-Turanian plant geographical region and the Saharo-Arabian region with some Mediterranean components (Danin et al. 1975; Olsvig-Whittaker et al. 1983; Yair and Danin 1980; Yair and Shachak 1982; Zohary 1962). The study area has a range of communities from semi-desert (10–30 % perennial shrubs and semi-shrubs) on the rocky upper north exposed slopes, which are characterized by an unfavorable water regime (Yair and Danin 1980), to some patches of true desert vegetation (less than 10 % perennial cover) on the lower colluvium and southerly exposed slopes. The most favorable water regime prevails in soil pockets and crevices; therefore, vegetation is more or less concentrated along the soil patches and bedrock joints filled with soil. Hence, the study site is very well suited to determine the role of surface ecohydrology for SOC stocks.

3 Methods

Based on the aims of the study, the following objectives for field sampling and data analysis are derived: (1) to sample slope sections with different ecohydrologic characteristics (soil and vegetation) to calculate SOC stocks; (2) to compare soil properties, vegetation, SOC concentrations, and SOC stocks for the different ecohydrologic units; and (3) to identify the factors which determine SOC stocks on rocky desert slopes.

3.1 Ecohydrologic units along rocky desert slopes at Sede Boker

The study site was mapped based on differences in surface conditions (such as geology, rock/soil ratio, soil distribution, soil bedding, soil depth), microclimate (as indicated by slope gradient and aspect), and vegetation according to Olsvig-Whittaker et al. (1983), Schreiber et al. (1995), and Yair and Raz-Yassif (2004). These factors control the water availability for vegetation and thus determine the ecohydrologic units (EHUs) along the rocky desert slopes. The following units were distinguished for soil sampling and vegetation mapping (Table 1): (1) flat desert pavement (FDP), (2) gently sloped desert pavement (SDP), (3) non-fissured bedrock slope (BS), (4) stepped and fissured bedrock slope (FBS), and (5) slope and valley colluvium (SVC). A detailed description of each unit is given in Table 1. The FDP represents the uppermost unit in the study site, which represents the flat plateau in which the basin is incised. It is characterized by a medium soil and vegetation coverage (~30 %). The SDP forms the transition from the FDP to the incised valley. It has a higher soil and vegetation coverage, which is conditioned through the accumulation of aeolian deposits. The bedrock slope, which is located below the SDP, is subdivided into stepped fissured (FBS) and non-fissured bedrock (BS). The FBS shows a characteristic stepped topography with a localized soil cover in small soil pockets and noncontinuous soil strips. The former forms in zones of structural weakness in the Shivta formation and the latter are deposits of fine sediment at the base of the bedrock step below the soil pockets (Yair and Shachak 1982). The vegetation coverage in this unit is generally high. The BS is a massive unit of bedrock with a low density of deep cracks. Soil cover in this unit is generally very shallow and covers only 5–10 %. The colluvium, at the base of the slope, can be distinguished in slope colluvium and valley colluvium (SVC). This unit is characterized by a continuous deposition of colluvial sediments, which provide the parent material for the formation of soil. However, soil coverage is still limited due to the presence of large rocks, which cover a significant portion of the surface and inhibit the growth of vegetation and soil formation.

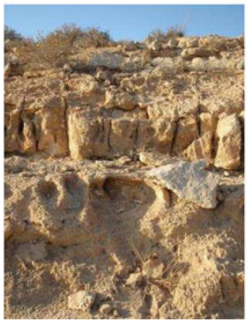
The ecohydrology of these units is strongly influenced by their surface characteristics. Therefore, the soil coverage was classified for each ecohydrologic unit using six soil-cover classes (I: <1 %; II: 1–2 %; III: 2–5 %; IV: 5–10 %; V: 10–30 %; and VI: >30 %) in the field (compare AG Bodenkunde 2005) and by visual interpretation of photos taken normal to the surface. Rocks larger than 20 cm, which cover the surface and prevent the growth of vegetation, were considered as "bedrock" and were excluded from soil coverage.

Vegetation was mapped and estimated for each ecohydrological unit based on the Braun-Blanquet (McAuliffe 1990) method as well as the plant guide of Zohary (1962) (see Table 1). The vegetation coverage was calculated on total surface (including rock and soils). Larger vegetation coverage than soil coverage is possible due to the canopy effect of the vegetation. Furthermore, we differentiated between the northwest and south exposed slopes, because according to Olsvig-Whittaker et al. (1983), an effect of solar radiation on soil moisture and vegetation and thus on evaporation can be expected on these slopes (Table 2).

3.2 Soil sampling and data analysis

To estimate SOC stocks, we took 82 soil samples covering all ecohydrologic units described above at the northeast and south-facing slopes. The number of samples per ecohydrologic unit was arranged to ensure a sufficient amount of samples for each set of relevant ecohydrologic surface properties along a slope (see Table 2). Soil sampling was conducted along a N–S transect through the studied valley at sampling sites across each ecohydrologic unit (see Fig. 1) in regular depth intervals (0–5, 5–15, 15–20 cm), continuing in

Table 1 Observed and mapped properties of the ecohydrologic units in the study area Sede Boker according to the findings of Olsvig-Whittaker et al. (1983), Schreiber et al. (1995), and Yair and Shachak (1982). Mean soil depth refers to areas covered by soil, and the rock/soil ratio is calculated as (100−soil cover)/soil cover

Ecohydrologic unit / general characteristics	Ecohydrologic unit	Mapped characteristics
Flat desert pavement (FDP) Uppermost unit with thinly bedded limestone and flint concretions Very shallow patchy soil and low vegetation coverage Dominant lithology: upper Netser formation		Slope: 6 % Soil cover: 30 % Soil depth: 15.76 cm Vegetation coverage: 10 % Rock/soil ratio: 2.33 pH (H_2O): 8.19 SOC_c (g 100 g^{-1}): 0.46 SIC (g 100 g^{-1}): 6.29
Gently sloped desert pavement (SDP) Forms the transition zone from the flat desert pavement to the incised valley Higher soil and vegetation coverage than FDP, accumulation of aeolian deposits Dominant lithology: upper Netser formation		Slope: 15 % Soil cover: 27.5 Soil depth: 18.75 cm Vegetation coverage: 22 % Rock/soil ratio: 2.63 pH (H_2O): 7.76 SOC_c (g 100 g^{-1}): 1.08 SIC (g 100 g^{-1}): 4.33
Stepped and fissured bedrock slope (FBS) Thinly bedded and densely fissured formation with stepped topography Soil accumulated in two different environments: (1) concentrated in crevices and fissures (2) accumulated in non-contiguous soil patches (Yair and Shachak 1982) Dominant lithology: lower Netser and upper Shivta formation		Slope: 20 % Soil cover: 45 % Soil depth: 20.52 cm Vegetation coverage: 32 % Rock/soil ratio: 1.22 pH (H_2O): 7.95 SOC_c (g 100 g^{-1}): 1.09 SIC (g 100 g^{-1}): 4.73

intervals of 20 cm where possible until the profile met bedrock). In addition to SOC concentrations, information of corresponding soil depth, bulk density, and coarse fraction are necessary to estimate SOC stocks (Eq. 1). Soil was sampled with a soil core sampler with a given volume (100 cm^3), which allowed the estimation of the soil bulk density BD (g cm^{-3}) based on the total soil weight (in grams) and the volume of the cylinder (in cubic centimeters) (Ravindranath and Ostwald 2008; Rodeghiero et al. 2009). The coarse fraction CF (g 100 g^{-1}) was calculated by the weight of coarse grains (>2 mm) divided by the total weight of the sample. At sampling sites with very shallow soils, such as weathering planes or depositional patches at the base of the steps, a mixed bag sample of 150 g was collected for a certain sampling area. In this case, the bulk density was estimated by multiplying the sampling area with the mean soil thickness of the sample.

3.3 Laboratory and statistical SOC analysis

Soil analysis was conducted in the laboratories of the University of Basel, Switzerland. The samples were

Table 1 (continued)

Ecohydrologic unit / general characteristics	Ecohydrologic unit	mapped characteristics
Non-fissured bedrock slope (BS) Extensive bedrock outcrops of massive limestone with low density of deep cracks Bedrock weathers into cobbles and boulders Soil shallowly accumulated as small soil patches Dominant lithology: upper Drorim formation		Slope: 21 % Soil cover: 7.5 % Soil depth: 10 cm Vegetation coverage: 9 % Rock/soil ratio: 12.33 pH (H_2O): 8.14
		SOC_c (g 100 g^{-1}): 0.61 SIC (g 100 g^{-1}): 4.37
Slope and valley colluvium (SVC) Soil bedding can be described as a colluvial mantle Densely jointed and covered with an colluvial mantle (Dan et al., 1972) Dominant lithology: lower Drorim formation		Slope: 18 % Soil cover: 45 % Soil depth: 28.66 cm Vegetation coverage: 23 % Rock/soil ratio: 1.22 pH (H_2O): 8.23 SOC_c (g 100 g^{-1}): 0.72 SIC (g 100 g^{-1}): 5.26

Table 2 Mean soil depth (related to soil-covered areas), median soil, and vegetation coverage and minimum, median, mean, max, and standard deviation of SOC stocks with respect to aspect and ecohydrologic units. The ecohydrological units in the table are ordered according to their sequence along the studied transect (compare Fig. 1). *N* northern aspect, *S* southern aspect, *FDP* flat desert pavement, *SDP* gently sloped desert pavement, *FBS* stepped and fissured bedrock slope, *BS* non-fissured bedrock slope, *SVC* slope and valley colluvium

Aspect	Ecohydrologic unit	No. of samples	Soil depth (cm)	Soil coverage (%)	Vegetation coverage (%)	$SOC_{stock,ehu}$ (kg C m^{-2})				
						Min	Median	Mean	Max	STD
N	FDP	9	15.3	30	10.5	0.13	0.26	0.28	0.74	0.18
N	SDP	23	12	40	21	0.06	0.56	0.72	1.90	0.55
N	FBS	7	17	45	35	0.68	1.21	1.42	3.04	0.78
N	BS	5	12	5	–	0.08	0.09	0.12	0.25	0.07
–	SVC	6	28.7	45	23	0.07	0.85	0.93	1.81	0.72
S	BS	8	14	10	–	0.03	0.07	0.07	0.13	0.04
S	FBS	14	19	45	12	0	0.59	0.71	2.37	0.63
S	SDP	3	23.1	15	5	0.02	0.22	0.17	0.26	0.13
S	FDP	7	24.7	30	–	0.05	0.15	0.21	0.39	0.13
	Total	82	18.7	29.4	24	0	0.31	0.58	3.03	0.61

initially dried at 40 °C and afterwards sieved using a stack of sieves to separate the coarse fraction (>2 mm), the fine fraction (<2 mm), and the fraction smaller than 0.032 mm. The latter was subject to further particle size analyses carried out with a SediGraph (SediGraph 5100, Micromeritics). That way, information about the clay fraction was obtained to test its influence on SOC stocks. SOC concentrations were measured using a LECO 100 CHN analyzer. First, total C content was measured with the untreated samples. Second, we estimated the SOC content based on the loss of ignition with 500 °C. Third, we calculated the soil inorganic carbon content for the same sample (without organic matter after burning) using again the CHN analyzer. For each representative layer i of a soil sample with thickness $d_{\mathrm{soil,\ i}}$ (in centimeters), SOC stock ($\mathrm{SOC}_{\mathrm{stock,\ i}}$, in kilograms of carbon per square meter) was estimated based on Eq. (2):

$$\mathrm{SOC}_{\mathrm{stock,\ i}} = 0.1 \times d_{\mathrm{soil,\ i}} \times \mathrm{BD} \times \mathrm{SOC}_{\mathrm{ci}} \times (1 - \mathrm{CF_i}/100) \tag{2}$$

SOC stocks ($\mathrm{SOC}_{\mathrm{stock}}$) per sampling site were then calculated by summarizing the SOC stock of each layer i at the corresponding sampling site:

$$\mathrm{SOC}_{\mathrm{stock}} = \sum \mathrm{SOC}_{\mathrm{stock,\ i}} \tag{3}$$

Based on Eq. (3), SOC stocks are not integrated over a certain reference depth, but for the entire soil column. To consider the limited soil coverage in each ecohydrological unit, we multiplied the stocks given in Eq. (3) with the mean soil coverage of each unit:

$$\mathrm{SOC}_{\mathrm{stock,\ ehu}} = \mathrm{SOC}_{\mathrm{stock}} \times \mathrm{soilcoverage} \tag{4}$$

To test the influence of the ecohydrologic units on SOC storage, the factors in the SOC-stock equation (Eq. (3) and the $\mathrm{SOC}_{\mathrm{stock,\ ehu}}$ (Eq. (4) estimates for each ecohydrologic unit were compared using box–whisker plots. The Kruskal–Wallis test was used to compare the variability of soil properties between ecohydrologic units with the variability within the units. The non-parametric Wilcoxon test for non-normally distributed variables was additionally used to test for differences of SOC stocks between pairs of ecohydrologic units. In the case of significant difference between the ecohydrological units (e.g., higher variability between the units than within the units), calculated p values are lower than 0.05 (equal to a level of significance of 5 %). For each ecohydrological unit, averages and standard deviation for each soil property were calculated. The spatial variations were evaluated by the coefficient of variation CV, which is given by the ratio of the standard deviation to the mean value of each soil property. The CV therefore allows the comparison of the variations of each soil property in different ecohydrologic units through the normalization of the standard deviation.

4 Results

4.1 Variability of SOC stocks and controlling soil properties

The results regarding the minima, mean, median, maxima, and standard deviations of the measured soil properties (BD, CF, $\mathrm{SOC_c}$, and d_{soil}) and the calculated SOC stocks are summarized in Tables 2 and 3. The largest variability of all SOC-stock controlling variables is displayed by the coarse fraction (CF factor in Eq. (1)), which ranges between 0 and 45.4 g 100 g^{-1} with a mean of 12.0 g 100 g^{-1} and a coefficient of variation of 81 %. $\mathrm{SOC_c}$ shows the second largest variability of the independent variables in Eq. (1), ranging from 0 to 4.48 g 100 g^{-1}, with a mean value of 0.86 g 100 g^{-1} and a coefficient of variation of 78.8 %. Soil depths range between 5 and 60 cm with a CV of 59.5 %. The lowest variability of the independent variables in Eq. (1) is shown by BD ranging between 0.56 and 1.90 g cm^{-3}, with a mean of 1.30 g cm^{-3} and a CV of only 20.7 % (see Table 3).

The large variability associated with the independent variables of BD, CF, $\mathrm{SOC_c}$, and d_{soil} is propagated through the calculation of the carbon stocks (Eqs. 1, 2, 3, and 4). Calculated SOC stocks show a wide variability ranging from 0 up to 3.03 kg C m^{-2}, with a mean of 0.58 kg C m^{-2} and a standard deviation of 0.61 kg C m^{-2}. The estimated CV of 105 %, which is the largest of the soil properties presented in Table 3, is mainly a result of the large spatial variability associated with the coarse fraction and the SOC concentration.

4.2 SOC stocks, soil properties, and ecohydrology

The median SOC concentration shows strong differences between the north- and the south-facing slopes (Fig. 3) and a tendency of increasing concentration downslope from the N-FDP to the N-FBS (Fig. 4a). As a combination of differences in aspect and the downslope increase, the greatest SOC concentrations are shown in the north-facing FBS (see Fig. 4q). Soil depths are higher on the S-facing slope and lowest on the N-facing slope (see Figs. 3c and 4b). Maximum soil depths and variability are observed in unit SVC, which is generally covered by a layer of colluvial deposits (up to 50 cm). Somewhat lower soil depths are observed at unit FDP of the northern exposed slope, while at the southern slope, this unit is characterized by higher values. As suggested by the Kruskal–Wallis test (p value= 0.19), differences of soil depth between ecohydrological units are not significant (see Fig. 4b). In contrast, significant

Table 3 Minima, median, mean, maxima, and standard deviation of measured soil properties relevant for the calculation of the SOC stock

Parameter	Min	Median	Mean	Max	STD	STD/mean (%)
BD (g cm^{-3})	0.56	1.30	1.30	1.90	0.27	20.7
CF (g 100 g^{-1})	0	10.38	12.02	45.42	9.74	81.0
SOC_c (g 100 g^{-1})	0	0.67	0.86	4.48	0.68	78.8
$SOC_{stock,\ ehu}$ (kg C m^{-2})	0	0.31	0.58	3.03	0.61	105.17
Soil depth (cm)	5	15	18.7	60	11.12	59.46

Values are calculated using the entire dataset (n=82). Mean soil depth refers to areas covered by soils. According to Eq. 4, SOC stocks refer to the entire area of the study site

differences of the $SOC_{stock,\ ehu}$ between the ecohydrologic units are confirmed by the p values derived from the Kruskal–Wallis test and the non-parametric Wilcoxon test (see Fig. 4c). The Wilcoxon test indicates that the EHUs cannot be stratified into clearly defined statistical groups according to their SOC stock. SOC stocks of the N-FBS unit are significantly higher than the other EHUs (expect for the SVC), but other EHUs do not classify into groups that are defined by major gaps of SOC stock in between. The trend along the transect (from N-FDP to S-FDP) is similar to the SOC concentration (see Fig. 4a) and dissimilar to the soil depths given in Fig. 4b. The mean vegetation coverage (see Fig. 4d and Table 2) is characterized by the largest differences between the aspect and the ecohydrologic units. The trend of the vegetation coverage along the different ecohydrologic units (see Fig. 4d) is similar to the trend of the SOC concentration and stock (see Fig. 4a, c). The lowest median vegetation coverage is observed at the southern SDP (5 %) and the highest median coverage at the northern exposed FBS (35 %) (see Fig. 4d and Table 2).

The clay fraction in all soil samples ranged from 9.05 to 16.61 %, with a mean of 13.23 % and a standard deviation of 2.32. No significant differences in average clay content between ecohydrologic units were identified, which suggests that clay content had only a minor effect on SOC stocks.

Measured SOC contents do not exhibit a notable vertical gradient at a point (Fig. 5). The SOC concentrations in the upper 40 cm of the soil are characterized by a strong variability, without any detectable trend. Below 40 cm, SOC concentrations are somewhat lower, with a smaller variability.

5 Discussion

5.1 SOC stock, surface characteristics, and vegetation

The very strong control of vegetation on the SOC concentration and $SOC_{stock,\ ehu}$ is revealed by their similar pattern on different aspects (see Fig. 3) and in the ecohydrologic units (see Fig. 4). Mean SOC concentrations and stocks strongly correlate with vegetation coverage in each ecohydrologic unit (R^2=0.8 and 0.9, respectively, Fig. 6a and b). The highest SOC concentration and $SOC_{stocks,\ ehu}$ are found at slope exposures that favor high soil moisture and thus

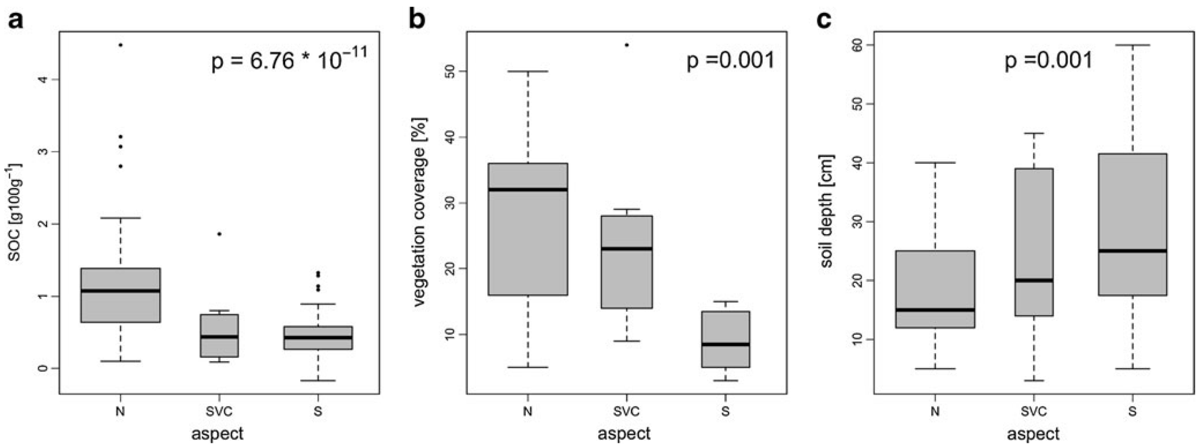


Fig. 3 SOC concentration (g 100 g^{-1}) (**a**), vegetation coverage (in percent) (**b**), and soil depth (in centimeters) (**c**) with respect to aspect from the whole investigation area. *N* and *S* indicated northern and southern aspects, respectively. The *boxes* have widths proportional to the number of sampling points in each box (number of total measurements, 82)

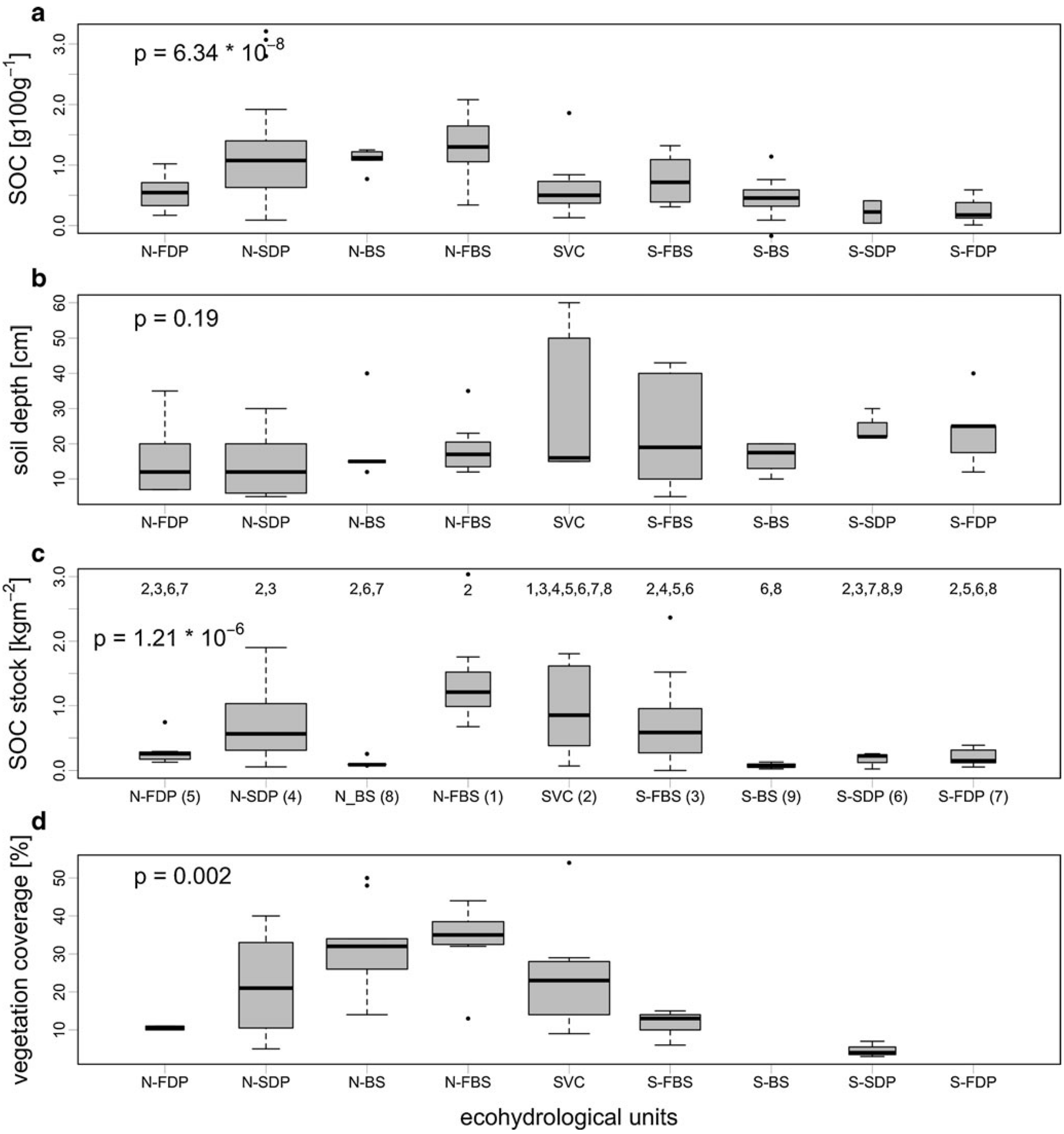


Fig. 4 **a** SOC concentration, **b** soil depths, **c** $SOC_{stock,\ ehu}$, and **d** vegetation coverage, **d** with respect to correspondence ecohydrologic unit and aspect. *N* and *S* indicated northern and southern aspect, respectively. *FDP* flat desert pavement with significant higher soil cover and depth due to minor slope gradient, *SDP* gently sloped desert pavement with lower soil depth due to higher slope gradient, *FBS* stepped and fissured bedrock slope, *BS* non-fissured bedrock slope, *SVC* slope and valley colluvium. Ecohydrologic units are ordered in correspondence to their locations from N to S along the transect. The *numbers* in brackets following the EHU names of Fig. 4c denote the rank of the EHU (e.g., the highest median of N-FBS is given by *(1)*, the lowest for S-BS given by *(9)*). The *numbers* above the *boxes* denote EHUs (according to their rank) with a similar SOC-stock distribution (as given by $p>0.05$ using the non-parametric Wilcoxon test). The *boxes* have widths proportional to the number of sampling points in each box (number of total measurements, 82). The *p* values are derived using the Kruskal–Wallis test and give significant differences between EHUs in case $p<0.05$

high vegetation densities (e.g., northern exposed slopes and lower slope positions, Figs. 3 and 4). In contrast, the mean soil depth of the ecohydrologic units correlates only very weakly with SOC concentration (see Fig. 6c), and no

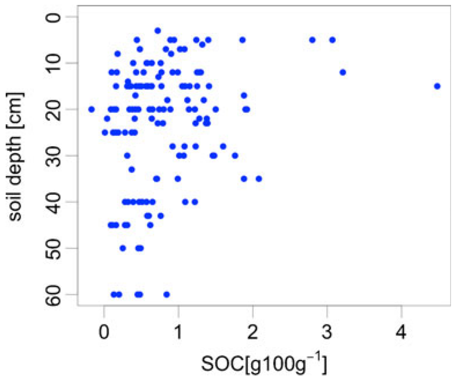


Fig. 5 SOC concentration as a function of depth below surface, plotted for every sample (n=82)

correlation is found between soil depth and $SOC_{stock,\ ehu}$ (see Fig. 6d). Thus, aspect-driven microclimatic effects that control soil moisture and vegetation coverage appear to affect SOC stocks more strongly than soil depth. The lacking relevance of soil thickness on rocky desert slopes is in strong contrast to its importance for SOC stocks in more humid areas (Berhe et al. 2008; Yoo et al. 2006). The positive relationship between vegetation coverage and SOC stocks at Sede Boker shows that the findings of Olsvig-Whittaker et al. (1983), who studied the effects of surface properties on vegetation, can also be applied to SOC stocks. Our results suggest that the different ecohydrologic conditions along rocky desert slopes near Sede Boker identified by Olsvig-Whittaker et al. (1983), Schreiber et al.

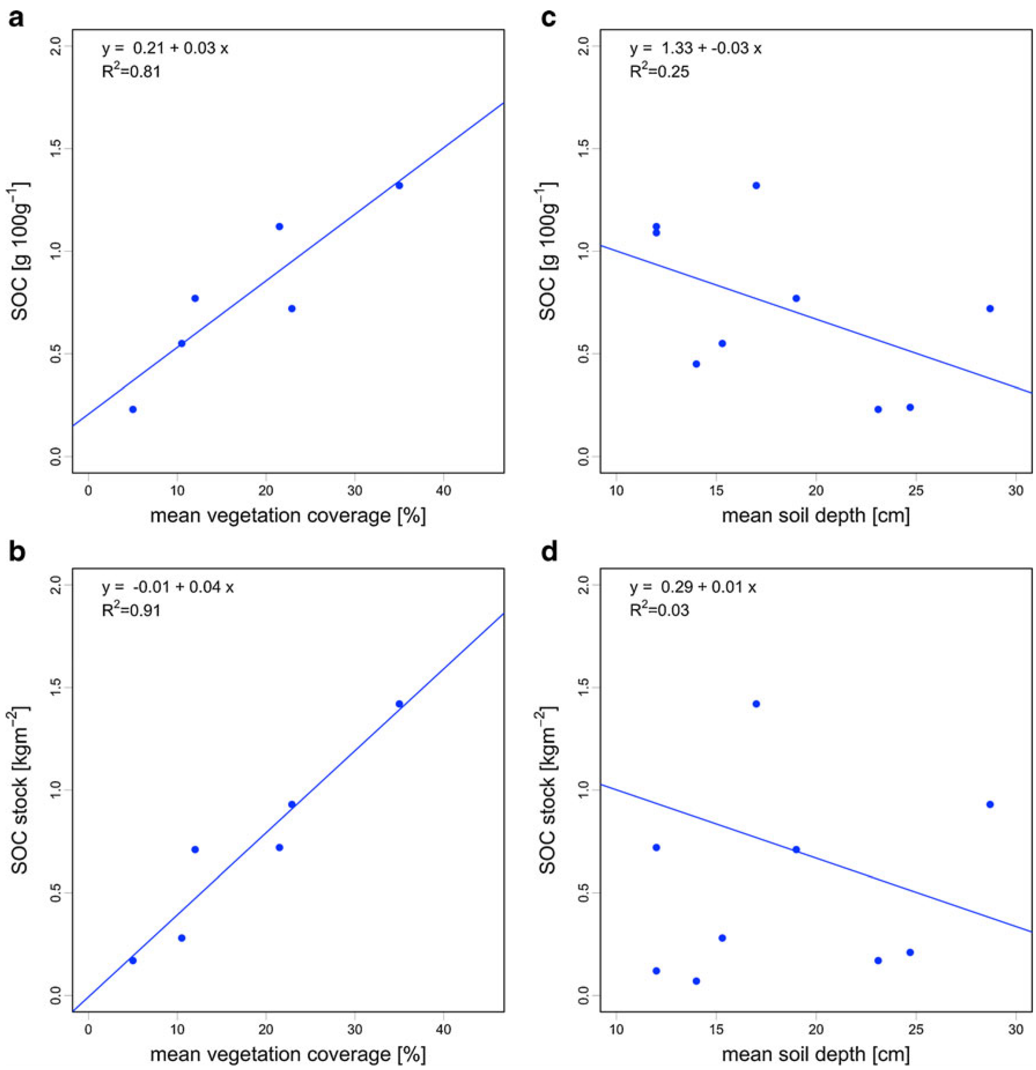


Fig. 6 Scatterplot of SOC concentration (**a**, **c**) and $SOC_{stock,\ ehu}$ (**b**, **d**) of sampled soils versus vegetation coverage and soil depth. Values are mean values obtained for each ecohydrologic unit

(1995), and Yair and Raz-Yassif (2004) also affect the SOC stocks on the different units. A similar effect is reported by Li et al. (2010) and Jobbágy and Jackson (2000) who both found a strong link between aboveground vegetation properties (e.g., density, type, stand age) and SOC. Our results also suggest that vegetation coverage provides a direct index for the spatial pattern of SOC stocks in drylands.

5.2 Surface processes and SOC stocks

The variability of the soil properties and the SOC stocks at Sede Boker is associated with differences in slope aspect (see Fig. 3) and NPP of the ecohydrologic units along the rocky desert slopes (see Fig. 4, Tables 2 and 3). In accordance with Olsvig-Whittaker et al. (1983), these results imply a positive dependency of SOC stocks on the relative moisture supply, which is given by surface runoff and aspect-driven differences of evaporation. The discontinuity of runoff associated with the patchwork of water sources and sinks also affects the distribution of SOC in the soil profile. In undisturbed soils, a strong vertical SOC gradient between topsoil and bottom soil is common (Arrouays and Pelissier 1994; Mishra et al. 2009; Wang et al. 2004). At Sede Boker, fine sediments provide the bulk substrate for soil formation and are preferentially deposited in small depressions and bedrock fissures, which act as local sediment sinks (see Figs. 1 and 2) (Olsvig-Whittaker et al. 1983; Yair and Danin 1980). Soil depth therefore varies on a centimeter to meter scale due to the spatial pattern of bedrock surface morphology. Eroded topsoils, which are generally enriched in SOC, are deposited in these fissures and may be stored over a long period of time. The limited change of SOC concentration with depth (see Fig. 5) at our sampling sites is in agreement with strong SOC redistribution and deposition at Sede Boker. Thus, the relationship of SOC content and soil depth appears to be strongly influenced by lateral soil movement, highlighting the need to consider soil as a mobile layer, formed by selective erosion and deposition (Hoffmann et al. 2009; Kuhn et al. 2009), which varies in time through changing source areas and/or the changing soil conditions in the source area (Dotterweich 2008).

5.3 SOC-stock comparison with other drylands

Table 4 summarizes results of SOC studies in arid and semi-arid areas, regarding the measured SOC concentrations and stocks. The estimated $SOC_{stocks,\ ehu}$ of the Sede Boker study area are in a similar range, while SOC concentrations are generally greater than those in other arid environments (see Table 4). Because $SOC_{stocks,\ ehu}$ refer to the entire study site and SOC concentrations to places in which soils are developed, the similar spatial pattern of $SOC_{stocks,\ ehu}$ and

Table 4 Global comparison of SOC and SOC stocks in different arid environments

Reference	Region	Environment	MAP (mm $year^{-1}$)	Area (km^2)	Reference depth (cm)	SOC stock (kg C m^{-2})	SOC_c (g 100 g^{-1})
Schlesinger (1977)	Global	World desert soils		1.83×10^9	Not specified	0.023–0.055	
Amundson (2001)	Global	Warm desert		14×10^6	Not specified	1.4	
Watson et al. (2000)	Global	Deserts and semi-deserts		45.5×10^6	0–100	4.37	
Feng et al. (2002)	Land regions of China	Different desert types	46–800	Variable	0–100	0.02–12.52 (mean, 2.32)	
Feng et al. (2002)	Land regions of China	Different desert types	46–800	Variable	0–20	0.02–4.97 (mean, 1.12)	
Balpande et al. (1996)	Central India	Vertisols	877–975	Profile measurement	Not specified		0.1–0.4
Zak et al. (1994)	Mexico, S-USA	Chihuahuan desert	240	Point measurement	Not specified		0.16
Bolton et al. (1993)	SE Washington, USA	Sagebrush steppe	100–250	Point measurement	Not specified		0.08
Perkins and Thomas (1993)	Kalahari, Botswana	Kalahari desert	150–600	Point measurement	Not specified		0.2–0.6
Ardö (2003)	Sudan	Semi-arid Sudan	200–800	2.62×10^6	0–20	0.06	
Zaady et al. (1996)	Negev, Isreal	Negev desert	200	Point measurement	Not specified		0.45–0.56
Fliessbach et al. (1994)	Negev, Israel	Negev desert	90 (19.5–180)	Point measurement	Not specified		0.03
This study	Sede Boker Negev, Israel	Rocky desert	91 (34–167)	0.045	Variable	0.31 (0.0–3.03)	0.67 (0.0–4.48)

MAP mean annual precipitation

increased SOC concentrations are attributed to the patchiness of soil cover in our study area compared to other areas cited in Table 4. While large fractions of our study area have rocky surfaces, sites with soil cover also carry vegetation and thus increased SOC concentrations. This is in accordance to the "islands of fertility" (Schlesinger and Pilmanis 1998) with increased biogeochemical processes, NPP, and SOC concentrations. Furthermore, higher concentrations in our study site might be attributed to the reduced mineralization of SOC, due to the lack of water in the Negev desert (Yao et al. 2010) and/or the degradation of soil due to overgrazing (compare for instance Bolton et al. 1993) in some of the other sites mentioned in Table 4. The comparison of our study to those presented in Table 4 remains limited. The studies presented in Table 4 rely on different measurement techniques of the SOC, different upscaling approaches, and variable reference soil depths taken into account. Unfortunately, reference soil depths are only given for 4 of the 13 case studies. Differences in SOC stocks may thus not represent environmental conditions, but simply the different methodologies applied for inventorying. The comparison indicates that the number of high-resolution SOC inventories in arid environments is very limited, and more case studies using a comparable methodology are necessary to evaluate the importance and potential changes of SOC in arid environments. In any case, on a global scale, the relatively large $SOC_{stocks,\ ehu}$ in our study area indicates that soils in arid environments, especially in rocky deserts associated with hardly any soil cover, may comprise a significant SOC pool that is sensitive to NPP. Even the admittedly somewhat arbitrarily calculated average soil depth of 18 cm is also in contrast to the notion that rocky deserts do not contain significant soil cover and thus SOC.

6 Conclusions

This study aimed at identifying the relationship between surface characteristics, vegetation coverage, and SOC concentration and stocks in the arid northern Negev in Israel. Soils cover 30 % of the study area, and the soil-covered areas are on average 18 cm deep and contained similar concentrations of SOC than soils from more humid drylands. However, the results show a large spatial variability of SOC, soil bulk density, and soil thickness. Consequently, the estimated SOC stock ranges between 0 and 3.03 kg C m^{-2} with a mean of 0.58 kg C m^{-2} (median, 0.31 kg C m^{-2}) and a standard deviation of 0.61 kg C m^{-2}. The differences in SOC stocks between ecohydrologic units on the north- and south-facing slopes indicate the relevance of eco-climate and thus the potential impact of climate change on rocky desert SOC stocks. They confirm that conceptual approaches, which explain the spatial patterns of vegetation cover on rocky desert slopes in the Negev, can also be applied to SOC stocks. In addition to climate-driven differences between aspect and slope position, the ecohydrologic units take changes of small-scale surface properties into account. The small-scale variability is mainly caused by lithology-driven differences of the microtopography, which provides accommodation space in fissures and on bedrock steps, for fine sediment accumulation and soil formation. Thus, significant differences of SOC stocks as well as vegetation densities between ecohydrologic units demonstrate that small-scale surface properties modulate climate-driven differences and provide a further control on the presence or absence of soils and thus on the amount of SOC storage.

In more general terms, our results show that dryland soils contain a significant amount of SOC even in arid regions. Even this amount is smaller than in more humid environments; it is of major importance for the functioning and thus conservation of arid ecosystem. Differences in eco-climate, microtopography, surface processes, soil formation and properties, and vegetation between the ecohydrologic units are apparently of greatest importance for SOC stocks in drylands. The results strongly suggest that the microscale (decimeter to meter) water supply and NPP, as indicated by the vegetation coverage, determine SOC stocks on rocky desert slopes. The variability of SOC stocks, driven by aspect, soil moisture availability, and vegetation coverage, also implies that SOC stocks in arid environments are highly sensitive to climate change and thus represent a major unstable C pool within the global carbon cycle of the twenty-first century.

Acknowledgments We owe our gratitude to the Freiwillige Akademische Gesellschaft (FAG) Basel and the University of Basel for funding the field work in Sede Boker.

References

Amundson R (2001) The carbon budget in soils. Ann Rev Earth Planet Sci 29:535–562

Ardö JLO (2003) Assessment of soil organic carbon in semi-arid Sudan using GIS and the CENTURY model. J Arid Environ 54:633–651

Arkin Y, Braun M (1965) Type sections of upper cretaceous formations in the northern Negev (southern Israel). Israel Geol. Survey Stratigraphic Section, No.2a, Jerusalem, pp 1–19

Arrouays D, Pelissier P (1994) Modeling carbon storage profiles in temperate forest humic loamy soils of France. Soil Sci 157:185–192

Asner GP, Borghi CE, Ojeda RA (2003) Desertification in Central Argentina: changes in ecosystem carbon and nitrogen from imaging spectroscopy. Ecol Appl 13:629–648

Balpande SS, Deshpande SB, Pal DK (1996) Factors and processes of soil degradation in Vertisols of the Purna Valley, Maharashtra, India. Land Degrad Dev 7:313–324

Berhe AA, Harden JW, Torn MS, Harte J (2008) Linking soil organic matter dynamics and erosion-induced terrestrial carbon sequestration at different landform positions. J Geophys Res 113:1–12

AG Bodenkunde (2005) Bodenkundliche Kartieranleitung KA 5 (German Soil Mapping Guide, 5th edition), Bundesanstalt für Geowissenschaften und Rohstoffe und Geologische Landesämter der Bundesrepublik Deutschland (Federal Institute for Geosciences and Natural Resources and Geological Survey offices of the Federal Republic of Germany) (eds.), Hannover, pp. 438

Bolton H, Smith JL, Link SO (1993) Soil microbial biomass and activity of a disturbed and undisturbed shrub-steppe ecosystem. Soil Biol Biochem 25:545–552

Branchu P, Faure H, Ambrost JP, Bakker EMV, Fauredenard L (1993) Africa as source and sink for atmospheric carbon dioxide. Glob Planet Chang 7:41–49

Bruins HJ (1986) Desert environment and agriculture in the Central Negev and Kadesh-Barnea during historical times. Ph.D. thesis, Agricultural University Wageningen. Midbur Foundation, Nijkerk, the Netherlands

Dan J, Yaalon DH, Koyumdjiski H, Raz Z (1972) The soil association map of Israel. Israel J Earth Sci 21:29–49

Danin A, Orshan G, Zohary M (1975) The vegetation of the northern Negev and the Judean Desert of Israel. Israel J Bot Basic Appl Plant Sci 24:118–172

Dotterweich M (2008) The history of soil erosion and fluvial deposits in small catchments of Central Europe: deciphering the long term interaction between human and the environment—a review. Geomorphology 101:192–208

Egli M, Sartori G, Mirabella A, Favilli F, Giaccai D, Delbos E (2009) Effect of north and south exposure on organic matter in high Alpine soils. Geoderma 149:124–136

Evenari M, Masig D, Rogel A (1980) Runoff-farming in the Negev Desert of Israel (VI). Jacob Blaustein Institute for Desert Research, Sede Boker

Fang C, Moncrieff JB (2001) The dependence of soil CO_2 efflux on temperature. Soil Biol Biochem 33:155–165

FAO (ed) (2004) Carbon sequestration in dryland soil. World soil resources reports 102, Rome. Available at: http://www.fao.org/docrep/007/y5738e/y5738e00.htm. Accessed Febuary 2012

Farage P, Pretty J, Ball A (2003) Biophysical aspects of carbon sequestration in drylands. Seminar paper presented at University of Essex, Feb 3, 1–25 pp

Feng Q, Endo KN, Guodong C (2002) Soil carbon in desertified land in relation to site characteristics. Geoderma 106:21–43

Fliessbach A, Sarig S, Steinberger Y (1994) Effects of water pulses and climate conditions on microbial biomass kinetics and microbial activity in yermosol of Central Negev. Arid Soil Res Rehab 8:353–362

Glatzel S, Sommer M (2005) Colluvial soils and landscape position: field studies on greenhouse gas exchange and related ecological characteristics. Z Geomorphol 139:87–99

Glenn E, Squired V, Olson M, Frye R (1993) Potential for carbon sequestration in the drylands. Water Air Soil Pollut 70:341–355

Goidts E, van Wesemael B (2007) Regional assessment of soil organic carbon changes under agriculture in Southern Belgium (1955–2005). Geoderma 141:341–354

Grieve IC (2001) Human impacts on soil properties and their implications for the sensitivity of soil systems in Scotland. Catena 42:361–374

Griffiths RP, Madritch MD, Swanson AK (2009) The effects of topography on forest soil characteristics in the Oregon Cascade Mountains (USA): implications for the effects of climate change on soil properties. For Ecol Manag 257:1–7

Hoffmann T, Glatzel S, Dikau R (2009) A carbon storage perspective on alluvial sediment storage in the Rhine catchment. Geomorphology 108:127–137

Houghton RA (2007) Balancing the global carbon budget. Ann Rev Earth Planet Sci 35:313–347

IPCC (2007) Chapter 7: Couplings between changes in the climate system and biogeochemistry. In: Climate Change 2007: The physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge

IUSS Working Group WRB (2006) World reference base for soil resources 2006. World soil resources reports no. 103. FAO, Rome

Jobbágy EG, Jackson RB (2000) The vertical distribution of soil organic carbon and its relation to climate and vegetation. Ecol Appl 10:423–436

Kirschbaum MUF (2000) Will changes in soil organic carbon act as a positive or negative feedback on global warming? Biogeochemistry 48:21–51

Kuhn NJ, Yair A (2004) Spatial distribution of surface conditions and runoff generation in small arid watersheds, Zin Valley Badlands, Israel. Geomorphology 57:183–200

Kuhn NJ, Hoffmann T, Schwanghart W, Dotterweich M (2009) Agricultural soil erosion and global carbon cycle: controversy over? Earth Surf Proc Land 34:1033–1038

Laity J (2008) Deserts and desert environments. Wiley-Blackwell, Singapore, p 342

Lal R (2003) Carbon sequestration in dryland ecosystems. Environ Manage 33:528–544

Lal R (2005) Soil erosion and carbon dynamics. Soil Tillage Res 81:137–142

Lal R (2009) Sequestering carbon in soils of arid ecosystems. Land Degrad Dev 20:441–454

Lal R, Kimble JM, Stewart BA (2001) Importance of soil bulk density and methods of its measurement. In: Kimble JM, Follett RF, Stewart BA (eds) Assessment methods for soil carbon. CRC Press, Boca Raton, pp 31–44

Leifeld J, Bassin S, Fuhrer J (2005) Carbon stocks in Swiss agricultural soils predicted by land-use, soil characteristics, and altitude. Agr Ecosyst Environ 105:255–266

Li P, Wang Q, Endo T, Zhao X, Kakubari Y (2010) Soil organic carbon stock is closely related to aboveground vegetation properties in cold-temperate mountainous forests. Geoderma 154:407–441

McAuliffe JR (1990) A rapid survey method for the estimation of denisty and cover in desert plant communities. J Veg Sci 1:653–656

Michaelides K, Chappell A (2009) Connectivity as a concept for characterising hydrological behaviour. Hydrol Process 23:517–522

Mishra U, Lal R, Slater BK, Calhoun F, Liu D, Van Meirvenne M (2009) Predicting soil organic carbon stock using profile depth distribution functions and ordinary kriging. Soil Sci Soc Am J 73:614–621

Olsvig-Whittaker L, Shachak M, Yair A (1983) Vegetation patterns related to environmental factors in a Negev Desert watershed. Vegetation 54:153–165

Parsons AJ, Abrahams AD (eds) (2009) Geomorphology of desert environments, 2nd edn. Springer, New York

Perkins JS, Thomas DSG (1993) Spreading deserts or spatially confined environments? Land degradation and cattle ranching in the Kalahari Desert of Botswana. Land Degrad Rehabil 4:179–194

Qi Y, Xu M, Wu J (2002) Temperature sensitivity of soil respiration and its effects on ecosystem carbon budget: nonlinearity begets surprises. Ecol Model 153:131–142

Quinton JN, Govers G, Van Oost K, Bardgett RD (2010) The impact of agricultural soil erosion on biogeochemical cycling. Nat Geosci 3:311–314

Ravindranath NH, Ostwald M (2008) Carbon inventory methods. Handbook for greenhouse gas inventory, carbon mitigation and roundwood production projects. Advances in global change research 29. Springer Science + Business Media B.V, Dordrecht, 308 pp

Reifenberg A (1947) The soils of Palestine. Murby, London, p 106

Rodeghiero M, Heinemeyer A, Schrumpf M, Bellamy P (2009) Determination of soil carbon stocks and changes. In: Kutsch WLB,

Heinemeyer A (eds) Soil carbon dynamics. An integrated methodology. Cambridge University Press, New York, pp 49–75
Rosenbloom NA, Harden JW, Neff JC, Schimel DS (2006) Geomorphic control of landscape carbon accumulation. J Geophys Res 111:1–10
Rotenberg E, Yakir D (2010) Contribution of semi-arid forests to the climate system. Science 327:451
Sarmiento JL, Gruber N (2002) Sinks for anthropogenic carbon. American Institute of Physics
Schimel DS (2010) Drylands in the earth system. Science 327 (5964):418–419
Schimel D, Enting IG, Heimann M, Wigley TML, Raynaud D, Alves D, Siegenthaler U (1994) CO_2 and the carbon cycle. Extracted from the Intergovernmental Panel on Climate Change (IPCC Report, “Climate Change, 1994”). In: Wigley TMLS (ed) The carbon cycle. Cambridge University Press, New York, pp 7–36
Schimel D, Melillo J, Tian H (2000) Contribution of increasing CO_2 and climate to carbon storage by ecosystems in the United States. Science 287:2004–2006
Schlesinger WH (1977) Carbon balance in terrestrial detritus. Annu Rev Ecol Syst 8:51–81
Schlesinger WH (1990) Evidence from chronosequence studies for a low carbon-storage potential of soils. Nature 348:232–234
Schlesinger WH (1991) Biogeochemistry: an analysis of global change. Academic, San Diego, p 588
Schlesinger WH, Pilmanis AM (1998) Plant–soil interactions in deserts. Biogeochemistry 42:169–187
Schlesinger WH, Raikes JA, Hartley AE, Cross AF (1996) On the spatial pattern of soil nutrients in desert. Ecosyst Ecol 77:364–374
Schreiber KF, Yair A, Shachak M (1995) Ecological gradients along slopes of the Northern Negev Highlands, Israel. Catena Adv Geoecol 28:209–229
Seip HM (2001) We know too little about the carbon cycle. Cicerone (1), Oslo, p 6
Smith JE, Heath LS (2002) A model of forest floor carbon mass for United States forest types. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northeastern Research Station, Newtown Square PA. Research Paper NE-722, 37 pp
Tan ZX, Lal R, Smeck NE, Calhoun FG (2004) Relationships between surface organic carbon pool and site variables. Geoderma 121:187–195
Tsui C-C, Chen Z-S, Hsieh C-F (2004) Relationships between soil properties and slope position in a lowland rain forest of southern Taiwan. Geoderma 123:131–142
van Wesemael B, Paustian K, Meersmans J, Goidts E, Barancikova G, Easter M (2010) Agricultural management explains historic changes in regional soil carbon stocks. Proc Natl Acad Sci 107:14926–14930
Wang S, Huang M, Shao X, Mickler RA, Li K, Ji J (2004) Vertical distribution of soil organic carbon in China. Environ Manage 33:200–209
Watson RT, Noble IR, Bolin B, Ravindranath NH, Verardo DJ, Dokken DJ (eds) (2000) Land use, land-use change, and forestry. A special report of the IPCC. Cambridge University Press, Cambridge
Wigley TML, Schimel DF (eds) (2005) The carbon cycle. Cambridge University Press, Cambridge. 312 pp
Yaalon DH, Dan J (1974) Accumulation and distribution of loess-derived deposits in the semi-desert and desert fringe areas of Israel. Z Geomorphol 20:91–105
Yair A (1990) The role of topography and surface cover upon soil formation along hillslopes in arid climates. Geomorphology 3:287–299
Yair A (1992) The control of headwater area on channel runoff in a small arid watershed. In: Parsons AJ, Abrahams AD (eds) Overland flow: hydraulics and erosion mechanics. UCL Press, London, pp 53–68
Yair A (1994) The ambiguous impact of climate change at a desert fringe: Northern Negev, Israel, A.C. In: Millington AC, Pye K (eds) Environmental change in drylands: biogeographical and geomorphological perspectives. Wiley, Chichester, pp 199–227
Yair A, Danin A (1980) Spatial variations in vegetation as related to the soil moisture regime over an arid limestone hillside, Northern Negev Israel. Oecologia 47:83–88
Yair A, Raz-Yassif N (2004) Hydrological processes in a small arid catchment: scale effects of rainfall and slope length. Geomorpholohgy 61:155–169
Yair A, Shachak M (1982) A case study of energy water and soil flow chains in an arid ecosystem. Oecologia 54:389–397
Yao S-H, Zhang B, Hu F (2010) Biophysical controls over mineralization and sequestration of amended organic carbon in soil: effects of intensity and frequency of drying and wetting cycles. World Congress of Soil Science: Soil solutions for a changing world. Brisbane, Australia
Yoo K, Amundson R, Heimsath AM, Dietrich WE (2006) Spatial patterns of soil organic carbon on hillslopes: integrating geomorphic processes and the biological C cycle. Geoderma 130:47–65
Zaady E, Groffman P, Shachak M (1996) Litter as a regulator of N and C dynamics in macrophytic patches in Negev Desert soils. Soil Biol Biochem 28:39–46
Zak JC, Willig MR, Moorhead DL, Wildman HG (1994) Functional diversity of microbial communities: a quantitative approach. Soil Biol Biochem 26:1101–1108
Zhou ZY, Li FR, Chen SK, Zhang HR, Li G (2011) Dynamics of vegetation and soil carbon and nitrogen accumulation over 26 years under controlled grazing in a desert shrubland. Plant Soil 341:257–268
Zohary M (1962) Plant life in Palestine, Israel and Jordan. The Roland Press Co., New York, p 262

4. Assessment of variability and uncertainty of soil organic carbon in a mountainous boreal forest (Canadian Rocky Mountains, Alberta)

This chapter has been submitted in GEODERMA as: Hoffmann, U., Hoffmann, T., Johnson, E. A., Kuhn, N. J. (2012): Assessment of variability and uncertainty of soil organic carbon in a mountainous boreal forest (Canadian Rocky Mountains, Alberta). In review.

Abstract

Mountain environments are heterogeneous and dynamic geomorphic environments sensitive to land use and climate change. Heterogenic environmental conditions result in a large variability of mountain soil properties, and thus in large uncertainties of inventories of soil organic carbon (SOC). In this study we analyzed the variability of soil properties associated with the calculation of a SOC inventory in a mountain environment in the Canadian Rocky Mountains (Alberta). Therefore, we calculated the analytical uncertainty and spatial variability of SOC stocks using Gaussian error propagation and Taylor series expansion along seventeen 36 m long transects to identify major sources of uncertainty. The results indicate that bulk densities generated the largest uncertainty associated with the analytical precision. However, analytical uncertainties are much smaller than the uncertainty introduced by the spatial variability of the coarse fraction and SOC concentrations. This study contributes to insufficiently considered analysis of uncertainties in SOC stocks. Furthermore, we demonstrate the high potential of nested sampling approaches to identify sources of uncertainties of SOC stocks and propose to apply distributions of the coarse fraction in different geomorphic environments to reduce the uncertainties associated with heterogeneous mountain environments.

4.1 Introduction

Globally, soils are the largest terrestrial pool of carbon (C), storing approximately 1500 Pg C in the top 1 m (Batjes, 1996; Lal, 2004). Even small fluctuations of soil organic carbon (SOC) content due to changes in climate, land use or management practice, may result in a significant net exchange of C between the atmosphere and the pedosphere (IPCC, 2007; Mishra et al., 2009). Thus, understanding the role of soil C in the global carbon cycle requires detailed knowledge on the fluxes, amounts, and spatial patterns of SOC. Therefore, accurate quantification of SOC storage and its spatial patterns is of fundamental importance to global climate change modeling (Quinton et al., 2010; Zhao et al., 2005).

There is considerable uncertainty if mountain ecosystems, which cover roughly 20 % of the terrestrial Earth's surface, will act as a sink or source for future atmospheric CO_2 (Bockheim et al., 2000). Compared to soils at lower altitudes, very little is known about carbon storage in mountain soils, although these are especially vulnerable to climate change and constitute a substantial reservoir of organic C. Generally, lower temperatures and higher precipitation favor slow organic matter decomposition (Djukic et al., 2010; Price and Waser, 2000; Riedo et al., 2001). Hence, small changes in temperature and precipitation may release large amounts of CO_2, due to increased microbial activity in a warmer and wetter climate compared to recent conditions (Theurillat et al., 1998).

Generally, SOC stock inventories rely on relationships between SOC and potential controlling factors such as elevation and temperature (e.g. Bolstad and Vose, 2001; Djukic et al., 2010; Garcia-Pausas et al., 2007), aspect and slope position (e.g. Homann et al., 1995; Perruchoud et al., 2000), bedrock material and texture (e.g. Banfield et al., 2002; Brady and Weil, 2002; Hoffmann et al., 2009), pH (e.g. Falloon and Smith, 2009; Heckman et al., 2009), topography (e.g. Berhe et al., 2008; Yoo et al., 2006), vegetation and stand age of the forest (e.g. Luyssaert et al., 2008; Pregitzer and Euskirchen, 2004), and both human and natural disturbances (e.g. Czimczik et al., 2005; Morgan et al., 2010). Relations between soil properties and environmental variables are scale dependent and are generally derived from local measurements of soil properties and regional datasets that cover areas up to several thousand square kilometers (e.g. digital elevation models, soil maps, geological maps, and vegetation maps).

All SOC stock assessments are associated with large uncertainties that may result from: i) the complex interactions between the “independent” environmental variables, ii) the limited representation of small-scale variability of soil properties and soil forming processes at the scale of the SOC inventories, and iii) analytical uncertainties associated with the determination of SOC concentration, bulk density, and soil texture (Freibauer et al., 2004; Goidts et al., 2009). This is particularly true for mountain environments, which are characterized by a large spatial variability of the soil-forming factors and soil properties. Within a few meters large differences of the SOC content (in the order of 5 % to 20 %) may be observed. This small-scale heterogeneity is generally not represented by regional datasets, such as geological maps, soil maps, or digital elevation models (DEM), which typically have a resolution of 10-50 m (Lal, 2005b; Leifeld et al., 2005; Stutter et al., 2009). Consequently, improving SOC inventories requires identifying and reducing the sources of uncertainty that result from scale discrepancies between the operating soil-forming processes and the available regional datasets. First attempts have been made to quantify the uncertainty of regional SOC stock assessments in agricultural lowlands. For instance, Schwager and Mikhailova (2002) have illustrated the error propagation function for various sampling situations within one field and Goidts and van Wesemael (2007) presented a methodology to assess SOC stocks and their evolution at a regional scale in Belgium. In contrast to agricultural environments, little is known on the sources of uncertainty in mountain environments, where uncertainties are expected to be larger due to their pronounced topography. Major questions therefore remain regarding the relationship between topography and the spatial variability of SOC stocks, the identification of factors that significantly contribute to the uncertainty of SOC inventories, and the optimal sampling strategy for the SOC stock assessment in mountain terrain.

The main aim of this study is to estimate the uncertainty and error sources of SOC stocks in the Kananaskis Valley in the Canadian Rocky Mountains (Alberta). We first estimate the site-scale variability of relevant soil properties (bulk density, coarse fraction and SOC concentration) and SOC stocks in the mountainous study site. Second, we analyze the relation of SOC stocks to environmental characteristics that influence soil formation and SOC storage (elevation, slope, aspect, soil texture, stand age, lithology, geomorphic environment). Third, we analyze the unexplained variability caused by the limited resolution of the available data using a nested sampling approach. Therefore we quantify the variability within homogenous transects and analyze the propagation of analytical measurement errors and spatial differences based on Gaussian error propagation and Taylor series expansion (Schrumpf et al., 2011; Taylor, 1997). Finally, we identify the main sources of these uncertainties and provide implications for improving future sampling strategies in mountain environments.

4.2 Study site

The study site is located along Highway 40 within the Kananaskis River basin in south-western Alberta, about 110 km west of Calgary (Figure 4.1). The Kananaskis basin stretches from 115°30'W to 114°14'W and 51°07'N to 50°05'N and is located within the Front Ranges of the Canadian Rocky Mountains. Elevations range from 1315 m a.s.l. (at the outlet to the Bow River) to 3219 m a.s.l. (Mt. Rae at Highwood Pass) (Williams, 1990).

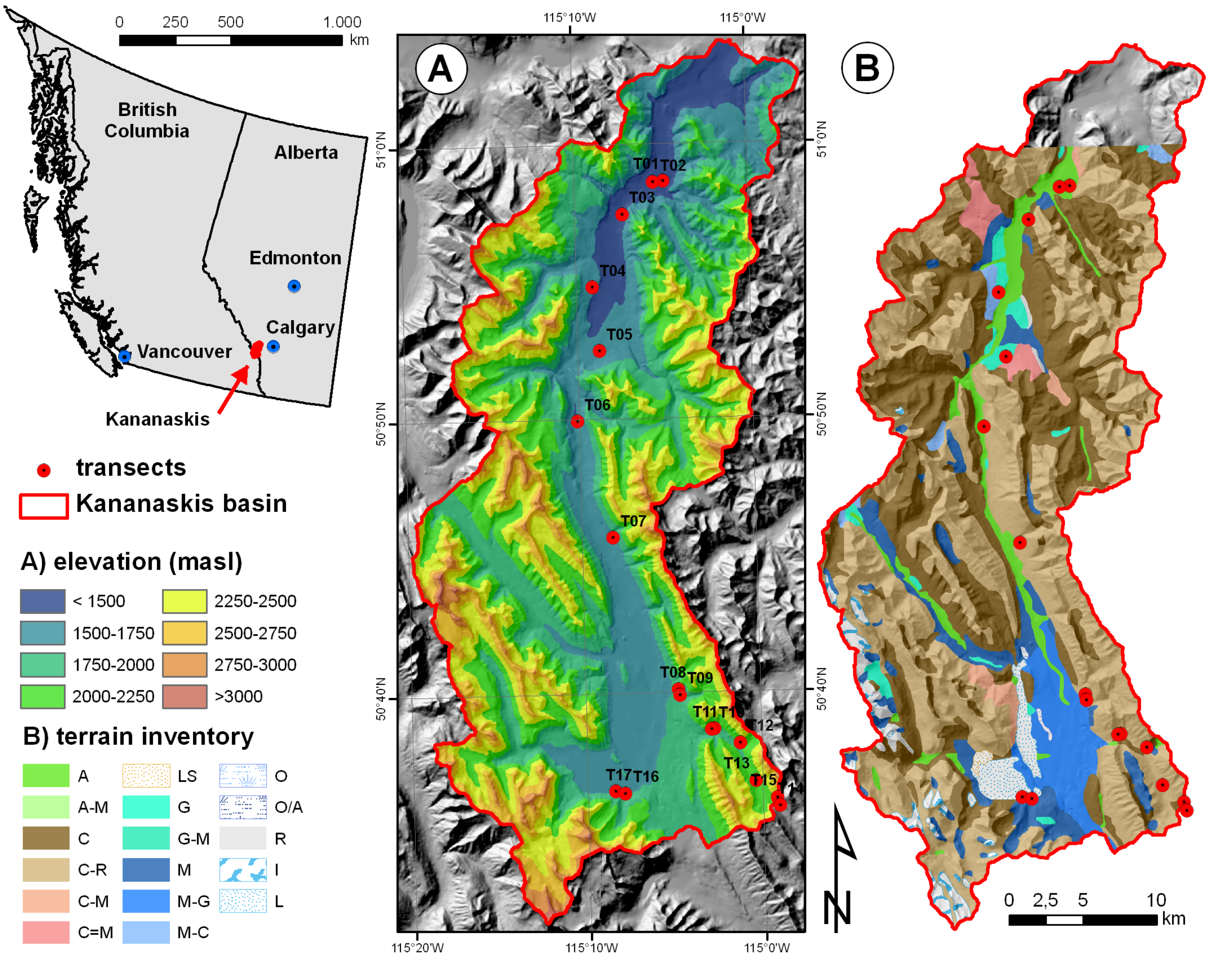


Figure 4.1: Location (left), topography (A), terrain inventory (B) of Kananaskis basin and sampling points (red points) within the study area. The terrain inventory is based on Jackson (1987). Following abbreviations are used for the terrain inventory: A = alluvial, M = moraine, G = glaciofluvial, C = colluvial, R = bedrock, O = organic, I = ice, L = lake, LS = landslide. C-R denotes shallow colluvial deposits on bedrock.

Mean annual precipitation in the Kananaskis valley (Meteorological Service of Canada, ID 3053600; elevation 1391 m a.s.l.) varies between 442 and 960 mm (average of 630 mm), with a maximum during May and June and a minimum during December and January. Precipitation varies throughout the valley, increasing from east to west and about 20 mm for every 100 m of elevation gain.

The topography, which is characterized by NNW-SSE aligned ridges and valleys (Figure 4.1), is strongly controlled by the orientation of thrust faults that are typical for the Rocky Mountain front ranges. The ridges are built up by Paleozoic carbonates, whereas the intervening valleys are formed of Mesozoic clastics. Thus, bedrock types of the studied slopes are either Devonian/Mississipian or Jurassic sandstones or siltstones. Predominant parent materials in the valleys are Triassic, Jurassic, Permian, and Upper Cretaceous shale and sandstones (McGregor, 1984).

Soil distribution and characteristics are strongly influenced by active geomorphic processes. Exposed, unweathered bedrock occurs frequently on slopes steeper than ~35°. The most prevalent source material for soils is colluvium veneer on slopes gentler than 35°. Colluvial slope deposits in the study area dominantly result from the weathering of bedrock, soil creep, rockfalls, and debris flow (McGregor, 1984).

Based on the Canadian system of soil classification (Greenlee, 1980), dominant soils in the study area are Brunisols, Regosols, as well as Gleysols and Organics (Greenlee, 1980). Brunisols, which are the most common soil type in the area, occur on steep slopes where water penetration is low and thus weathering of the soil is restricted. Regosols occur throughout a wide range of ecological conditions and are quite common in the study area. In water-saturated or near-saturated conditions in topographic depressions Gleysols and Organics may occur. Generally, soil horizons are weakly developed through the high activity of geomorphic processes (Greenlee, 1980).

The vegetation of the study area is dominated by natural forest. The subalpine vegetation is dominated by *Pinus contorta* Loudon (lodgepole pine), *Picea engelmannii* Parry ex Engelm. (Engelmann spruce), and *Abies lasiocarpa* (L.) Mill. (subalpine fir). The dominant deciduous tree species are *Populus tremuloides* (trembling aspen) and *Populus balsamifera* (balsam poplar).

Large fires in the Kananaskis region are predominantly lightning-caused and occur from July to the end of August. These fires are crown fires, characterized by high intensities and high rates of spread, which kill all trees and remove a large proportion of the organic layer (Fryer and Johnson, 1988). The fire return interval has varied over the last 300 years between ~90 to 150 years (Johnson and Larsen, 1991). Studies on fire behavior found the short fire return interval, constant hazard, and lack of spatial fire-frequency differences are the result of a regional climate control of the temporal fire frequency related to a characteristic synoptic weather pattern (Johnson and Wowchuk, 1993; Macias and Johnson, 2006).

4.3 Material and Methods

4.3.1 Sampling strategy

To analyze the SOC variability in the highly heterogeneous study area we used a two-level nested sampling approach (Stutter et al., 2009; Zhang, 2007; Zhang and McGrath, 2004). The relationship of soil properties and SOC stock with environmental conditions of the Kananaskis valley was established based on the selection of 17 sampling sites along Hwy 40 roughly a distance of 50 km (Figure 4.1).

Each site was described by its topographical position, geology, vegetation, and climate based on regional datasets. The terrain inventory map (map-scale: 1:125 000) (Jackson, 1987) allowed us to stratify sites into the following geomorphic environments: colluvial slope deposits, moraine, glaciofluvial, alluvial fan, and floodplain. Topographical position (including elevation, slope, and aspect) was obtained from a digital elevation model with a raster size of 30m. The DEM was interpolated from contour lines of the Canadian National Geographic database with a scale of 1:50.000. Geological information was taken from the geological map of the Rocky Mountain Foothills and the Front Ranges in Kananaskis Country (Geological Survey of Canada, map 1865A, map scale 1:100 000). Vegetation was characterized by its composition and age. Forest stand ages were taken from the 1:50 000 scale stand-origin map of the Kananaskis valley (Johnson and Larsen, 1991). The mean annual air temperature (MAAT) at each transect were estimated using a temperature gradient of 1°C per 100m elevation gain and a MAAT at the Kananaskis weather station of 6.5°C (values are derived from daily minimum and maximum temperatures measured from 1940 to 2010). Since no soil maps were available that cover the Kananaskis study area nor all 17 sampling sites, we did not consider soil maps as regional background information in this study.

The sampling sites were chosen to represent the distribution of the environmental site characteristics as given by the regional dataset and were placed if possible every 4 km along Hwy 40. The sampling sites range from 1403m above sea level (in the north of Hwy 40) to more than 2300 m a.s.l. (at the Highwood pass), and therefore represent the elevation of more than 84 % of the study area. Sampling sites are located at the valley bottom, the lower, middle and upper slopes of the study area. Based on the elevation gradient, the sampling site cover a MAAT-gradient from +5°C to -5°C (Table 4.1). Large-scale changes of SOC stocks between the study sites are assumed to be explained by differences of their environmental characteristics as given by the regional datasets.

Table 4.1: Site characteristics of sampled transects (T01-T17). Elevation, slope and aspect are derived from a 30 m digital elevation model. Forest stand ages (time since last forest fire) were taken from the 1:50 000 scale stand-origin map of the Kananaskis valley (Johnson and Larsen, 1991). Geomorphic environments are derived from the terrain inventory map (map-scale: 1: 125 000) based on Jackson (1987). Mean annual air temperature (MAAT) is calculated based on the MAAT of the Kananskis meteorological station at 1391 m above sea level (Meteorological Service of Canada, ID 3053600) and a temperature gradient of 1°C per 100 m elevation gain.

Transect	Elevation (m a.s.l.)	Slope	Aspect	Ecoregion	Stand age (yrs. AD)	Geomorphic environment	MAAT (°C)
T01	1403	2°	Level	Montane	1865	Alluvial	5.0
T02	1434	9°	NW	Montane	1909	Alluvial	4.7
T03	1403	0°	Level	Montane	1909	Alluvial	5.0
T04	1540	7.5°	E	Subalpine	1925	Glaciofluvial	3.5
T05	1535	0°	W	Subalpine	1881	Glaciofluvial	3.6
T06	1552	0°	Level	Subalpine	1881	Alluvial	3.4
T07	1682	17°	SW	Subalpine	1920	Colluvial	2.0
T08	1847	14°	NW	Subalpine	1920	Colluvial	0.3
T09	1843	20°	SW	Subalpine	1920	Colluvial	0.3
T10	1950	13°	S	Subalpine	1920	Colluvial	-0.8
T11	1932	5°	S	Subalpine	1920	Colluvial	-0.6
T12	1997	19°	SW	Subalpine	1858	Colluvial	-1.3
T13	2061	11°	W	Subalpine	1712	Colluvial	-2.0
T14	2210	13°	S	Subalpine	1920	Colluvial	-3.6
T15	2343	21°	S	Subalpine	1920	Colluvial	-5.0
T16	1734	19.5°	N	Subalpine	1866	Morainal	1.5
T17	1729	13°	N	Subalpine	1670	Morainal	1.5

The small-scale variability at each sampling site was quantified along a 36 m long transect with a primary core (PC) in the middle and six secondary cores to each side of the main point. The secondary cores (SC) were placed at logarithmic distance increments to the left (e.g. -16 m, -8 m, -4 m, -1.5 m, -0.75 m, -0.25 m) and right (+0.5 m, +1 m, +2 m, +5 m, +10 m and +20 m) of the PC along the transect (Simbahan et al., 2006). The orientation of the transects were chosen parallel to the slope at each sampling site (e.g. constant elevation of each sampling point within the transect). The length of the transects (36 m) was approximated by the resolution of the regional datasets (e.g. 30 m raster width of the digital elevation model). It is thus assumed that the variability of soil properties along the transect is not represented by the regional datasets and we refer this unexplained variability to the spatial uncertainty.

4.3.2 Soil sampling

Mineral soil samples were taken using a soil core (cylinder) with a diameter and height of 5 cm (98.2 cm^3). At each primary core an excavation pit was dug through the entire soil column. At this site, soil was sampled every 5 cm in the upper 20 cm and every 20 cm below 20 cm until the bedrock was reached. Soil sampling at each primary core was supplemented by a detailed profile description including horizon description, and the estimation of soil type, texture, color, and moisture using the Canadian soil classification system (Greenlee, 1980).

At the secondary cores sampling was limited to the upper 10 cm of the mineral soil. At all secondary cores two samples from the mineral A-horizon, generally at depths of 0-5 cm and 5-10 cm below the litter surface were taken.

At each sampling site, the litter layer was sampled using a cube (diameter = 5 cm), which was driven by hand through the entire litter layer.

4.3.3 Soil analyses

All soil samples were oven-dried at a temperature of 105°C and weighed. Afterwards mineral soil samples were sieved (<2 mm) to remove roots and rock fragments and to determine the weight of the coarse (≥2 mm) and fine (<2 mm) fractions. For each sample of the primary core the fraction <0.032 mm was subject to further particle size analyses carried out with a SediGraph (SediGraph 5100, Micromeritics); special attention was given to the clay fraction, which generally provides the strongest connection of the mineral soil and the *SOC* (Hartge and Horn, 2009; Wüthrich, 2004).

SOC was determined with a LECO analyzer (RC-612) based on a thermoanalytical analysis, which differentiates between the organic (SOC) and inorganic (SIC) carbon fractions by the specific temperature at which they oxidze. The release of organic carbon was measured at a constant temperature of 550°C. After the CO_2 concentrations droped to <1 % of the peak intensity, the sample was further heated up to 950°C at a rate of 120° per minute to measure the release of the inorganic fraction (RC612, 2006). SOC concentrations were then estimate through the time-integrated CO_2 concentrations.

4.3.4 Calculation of SOC stocks

The dry weight of the litter layer at each sampling site was multiplied with 0.37, according to Smith and Heath (2000), to convert the weight of the organic matter to the carbon stock of the organic horizon (OHC_{stock}):

$$OHC_{stock} = \text{dry weight} \times 0.37 \qquad \text{(equation 4.1).}$$

For each mineral soil sample in the ith horizon of the sampling site the $SOC_{stock,i}$ [kg cm^{-2}] was calculated according to equation 4.2 (Ellert et al., 2008; Schrumpf et al., 2011; Wang et al., 2004):

$$SOC_{stock,i} = 0.1 \times l_i \times BD_i \times SOC_i \times (1\text{-}CF_i / 100) \qquad \text{(equation 4.2)}$$

with:

l_i = thickness of representative sampling horizon [cm]

BD_i = soil bulk density [g cm^{-3}]

SOC_i = total organic carbon concentration [g g^{-1}]

CF_i = coarse fraction (fraction > 2 mm) [g g^{-1}].

SOC stocks per sampling site where then calculated by summarizing the $SOC_{stock,i}$ of each layer i at the corresponding sampling site (Ellert et al., 2002; Grossmann et al., 2001):

$$SOC_{stock} = \Sigma\, SOC_{stock,i} \qquad \text{(equation 4.3)}$$

For the primary cores, SOC stocks were calculated for 10 cm, and 30 cm (e.g. $SOC_{stock,10cm}$, $SOC_{stock,30cm}$). To evaluate the spatial variability and uncertainty of the soil properties and SOC stocks along the transects the SOC stock at the secondary points was first calculated for the upper 10 cm of the mineral soil. Secondly, the stock at each secondary core was extrapolated to 30 cm based on the ratio $SOC_{stock,30cm}$ /$SOC_{stock,10cm}$ at the primary core. Given SOC stock refer all to the reference depth of 30 cm.

4.3.5 Evaluation of uncertainties

Soil organic carbon stocks are associated with large uncertainties mainly resulting from: i) analytical measurement errors, and ii) the small-scale variability of soils and soil-forming processes. The calculation of SOC stocks relies on the measurement of total organic carbon concentration, the coarse fraction, the bulk density and the thickness of representative sampling horizon (equation 4.2). Each of these parameters are associated with analytical measurement errors and uncertainties regarding the small-scale variability of soils and soil forming processes. These uncertainties are propagated when calculating SOC stocks.

The uncertainty of *SOC* concentrations (ΔSOC) is given by the precision of the RC 612 and is assumed to be 10 % (see RC612, 2006). The uncertainty of the layer thickness Δl of the samples is based on replicate measurements of selected samples and is defined to be 10 % as well. The uncertainties of the coarse fraction and the bulk density (ΔCF and ΔBD) are calculated based on the Gaussian error propagation (Taylor, 1997):

$$\Delta BD = \sqrt{\left(\frac{\Delta f_t}{V}\right)^2 + \left(\frac{f_t}{V^2}\Delta V\right)^2} \quad \text{and} \quad \Delta CF = \sqrt{\left(\frac{\Delta f_g}{f_t}\right)^2 + \left(\frac{f_g}{f_t^2}\Delta f_t\right)^2} \qquad \text{(equation 4.4)}$$

where f_t and f_g are the weight of the total soil sample and the coarse fraction, respectively, and Δf_g und Δs_g are analytical uncertainties of f_t and f_g, which are given by the precision of the balance (±0.1 g). Likewise the uncertainty of the volume *V* of the sampling cylinder is assumed to be ΔV = 10 %.

To evaluate the analytical uncertainty of the SOC_{stock} (ΔSOC_{stock}) we used the Gaussian error propagation of equation 4.2, which is based on the uncertainties of the SOC concentration (ΔSOC), the coarse fraction (ΔCF), the bulk density (ΔBD) and layer thickness (Δl):

$$\Delta SOC_{stock,i} = (T_1^2 + T_1^2 + T_1^2 + T_1^2)^{1/2} \quad \text{and} \quad \Delta SOC_{stock} = \Sigma\, \Delta SOC_{stock,i} \qquad \text{(equation 4.5)}$$

where T_1 to T_4 are the individual contributions of ΔSOC, ΔCF, ΔBD and Δl to the total uncertainty of the SOC_{stock} and are given by:

$$\begin{aligned}
&\text{T1:} \quad \frac{\partial SOC_{stock}}{\partial SOC}\Delta SOC = (1-CF)\cdot BD\cdot l\cdot \Delta SOC \\
&\text{T2:} \quad \frac{\partial SOC_{stock}}{\partial CF}\Delta CF = SOC\cdot BD\cdot l\cdot \Delta CF \\
&\text{T3:} \quad \frac{\partial SOC_{stock}}{\partial BD}\Delta BD = SOC\cdot (1-CF)\cdot l\cdot \Delta BD \\
&\text{T4:} \quad \frac{\partial SOC_{stock}}{\partial l}\Delta l = SOC\cdot (1-CF)\cdot BD\cdot \Delta l
\end{aligned} \qquad \text{(equation 4.6)}$$

The second source of uncertainty arises from the variability of soil-forming processes, and the inability of regional proxy data (such as geological and soil map and digital elevation models) to represent the site-scale variability due to their limited resolution. Since the length of the transects (36 m) resembles the resolution of the used regional proxy data, scatter within the transects is not explained by these regional proxy data and is assumed to be related to the spatial uncertainty. The summarized effects of the unexplained spatial variability are given by the standard deviation of the relevant soil properties (e.g., SOC concentration, bulk density, and coarse fraction) within each transect.

To calculate the propagation of the spatial uncertainties for the resulting SOC stocks we used two approaches. The first approach relies on the Gaussian error propagation (equation 4.4 – 5.6) and thus resembles the calculation of the analytical uncertainties. In contrast to the calculation of the analytical errors, ΔSOC, ΔCF, ΔBD and Δl are given by the standard deviations within each transect. Since the same equations are used to estimate the propagated analytical and spatial uncertainty ΔSOC_{stock} they are directly comparable to each other. Thus, we used the Gaussian error propagation to independently evaluate the contribution of the analytical and spatial uncertainties. However, the application of the Gaussian error propagation is limited since it does not take into account the co-variances of the input parameters of equation 4.2. Co-variances may decrease or increase SOC stocks and should therefore be considered (Dileep et al., 2008). Therefore, we used a second approach that is based on the linear Taylor series expansion (Lo, 2005; Moelders et al., 2005), which has recently been applied to evaluate the uncertainties of carbon inventories by Goidts et al. (2009) and Schrumpf et al. (2011). The Taylor series expansion of equation 4.2, which defines the propagated spatial uncertainty of the SOC stocks, is given by Goidts et al. (2009):

$$\Delta SOC_{stock} = \frac{\Delta SOC^2}{SOC^2} + \frac{\Delta CF^2}{CF^2} + \frac{\Delta BD^2}{BD^2} + 2\left[\frac{\Delta SOC(1-CF)}{SOC(1-CF)} + \frac{\Delta SOC\cdot BD}{SOC\cdot BD} + \frac{\Delta BD(1-CF)}{BD(1-CF)}\right]$$

(equation 4.7)

where *ΔSOC*, *ΔCF*, *ΔBD* are the standard deviations of *SOC*, *CF* and *BD* and *ΔSOC (1-CF)*, *ΔSOC BD* and *ΔBD (1-CF)* are the co-variances within each transect.

4.4 Results

4.4.1 Spatial variability of soil properties

The averages and standard deviation (SD) of the measured and calculated soil properties for the reference depth of 30 cm depth for each studied transect T01 to T17 are summarized in Table 4.2.

Table 4.2: Mean and standard deviation (STD) of the measured and calculated soil properties up to 30 cm depth for each studied transect T01-T17 (compare Table 4.1 for considered environmental site characteristics for each transect). Gray shaded fields mark the minimum and maximum values for each soil property.

Transect	*SOC* [g g^{-1}]		*CF* [g g^{-1}]		*BD* [g cm^{-3}]		*SOC$_{stock}$* [kg C m^{-2}]		*OHC$_{stock}$* [kg C m^{-2}]	
	mean	STD	mean	STD	mean	STD	mean	STD	mean	STD
T01	0.034	0.010	0.17	0.13	0.97	0.21	5.22	1.76	3.69	1.53
T02	0.021	0.006	0.20	0.15	0.93	0.1	4.45	1.45	6.55	2.70
T03	0.040	0.015	0.00	0.00	0.80	0.20	8.25	1.37	13.50	8.10
T04	0.022	0.008	0.31	0.10	1.08	0.14	4.62	1.45	2.34	1.65
T05	0.013	0.002	0.22	0.10	1.11	0.13	2.03	0.36	3.01	1.42
T06	0.088	0.050	0.00	0.00	0.66	0.23	11.41	5.60	13.59	6.02
T07	0.031	0.008	0.30	0.15	0.99	0.21	6.52	3.49	1.86	1.60
T08	0.035	0.064	0.43	0.36	0.75	0.14	2.16	0.36	3.13	2.14
T09	0.039	0.008	0.68	0.15	1.13	0.13	3.40	0.76	2.15	1.11
T10	0.112	0.035	0.42	0.13	0.94	0.23	20.94	6.70	6.09	3.53
T11	0.072	0.019	0.42	0.72	1.00	0.24	11.37	5.92	4.41	1.22
T12	0.032	0.011	0.49	0.1	0.84	0.13	1.46	0.44	3.36	1.64
T13	0.033	0.009	0.36	0.15	0.99	0.14	1.99	0.61	7.79	2.51
T14	0.047	0.022	0.26	0.08	0.73	0.15	7.83	2.86	3.29	1.96
T15	0.034	0.013	0.27	0.01	0.98	0.16	5.76	1.15	4.66	2.72
T16	0.082	0.056	0.22	0.15	0.54	0.20	8.15	3.26	7.52	3.86
T17	0.041	0.012	0.42	0.19	0.72	0.12	2.95	0.45	6.54	3.38
all samples	0.045	0.035	0.36	0.38	0.89	0.23	6.40	5.58	5.51	4.70

The mean SOC concentration for the entire dataset is 4.5 % with a standard deviation of 3.5 % (the mean SIC is 0.9 % with a standard deviation of 1.7 %). The mean bulk density is 0.89 g m^{-3} with a standard deviation of 0.23 g cm^{-3}. *SOC$_{stock}$* values in the upper 30 cm range between 3.01 and 24.94 kg m^{-2}, with a mean and standard deviation of 6.40 kg m^{-2} and 5.58 kg m^{-2}, respectively. The coarse fractions average is 0.36 g g^{-1} with a large standard deviation of 0.38 g g^{-1}. The C stocks of the organic layer (*OHC$_{stock}$*) range between 2.15 kg m^{-2} and 13.95 kg m^{-2} with a mean and standard deviation of 5.51 kg m^{-2} and 4.70 kg m^{-2}, respectively. The thickness of the organic layer was smaller than 40 cm with a mean thickness of all sampling sites of 9.5 cm. As indicated in Figure 4.2, BD-values are normally distributed, *SOC* and SOC_{stock} are log-normally distributed. In contrast, CF-values are neither normally, nor log-normally distributed but shows a more heterogeneous distribution.

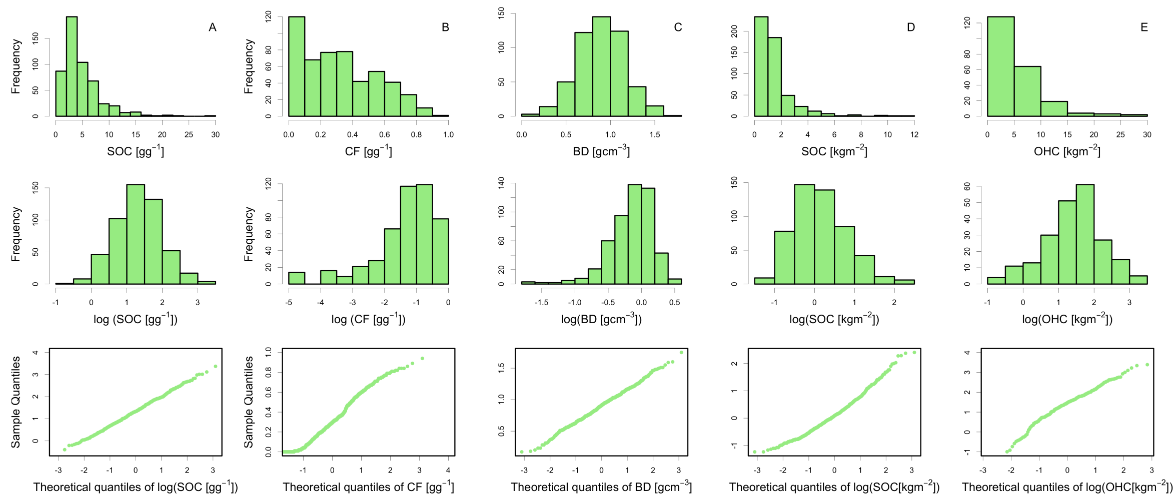


Figure 4.2: Distribution (normal values and log-transformed values) and quantile-quantile plots (qq-plots) of *SOC*, *CF*, *BD* and SOC_{stock}. qq-plots compare the ranked samples from the considered distribution with the quantiles of the normal distribution. In the case of normal distributed data, points in the qq-plots plot on a straight line.

The variability of the SOC concentration, coarse fraction, bulk density, SOC stock, and OHC stock within and between the transects is given in the boxplots (Figure 4.3). The transects are ordered with respect to their elevation, from lowest elevation on the left (1403 m at T01) to the highest elevation (2343 m at T15) on the right. The spatial variability demonstrate significant differences of the soil properties between the transects (Figure 4.3). Transect averages of SOC_{stock} range between 1.46 kg C m^{-2} (T12) and 20.94 kg C m^{-2} (T10). Even though there is a strong elevation gradient of 940 m between the lowest and the highest transect, there is no increasing trend of SOC concentration, SOC stock and OHC stock with increasing elevation.

Furthermore, there is no strong similarity of variability between the transects regarding any of the considered soil properties. The weak similarity of the variability of the SOC concentration (Figure 4.3A) and SOC_{stock} (Figure 4.3D) and the comparatively low variability of the *BD* indicate a stronger control of *SOC* concentration on transect variability of SOC_{stock} than the *CF* or *BD*. Transect averages of OHC_{stock} range between 2.15 kg C m^{-2} (T09) and 13.59 kg m^{-2} (T06), indicating that carbon storage in the O-horizon is similar to carbon storage in the mineral soil. The comparison of the distribution of carbon stocks in the O-horizon (Figure 4.3E) and the mineral soil shows diverging trends and suggests only a weak relationship between the organic and mineral horizons in the study area. However, the obvious differences of the soil properties between the transects suggest a strong influence of large-scale variability of the environmental characteristics of transects.

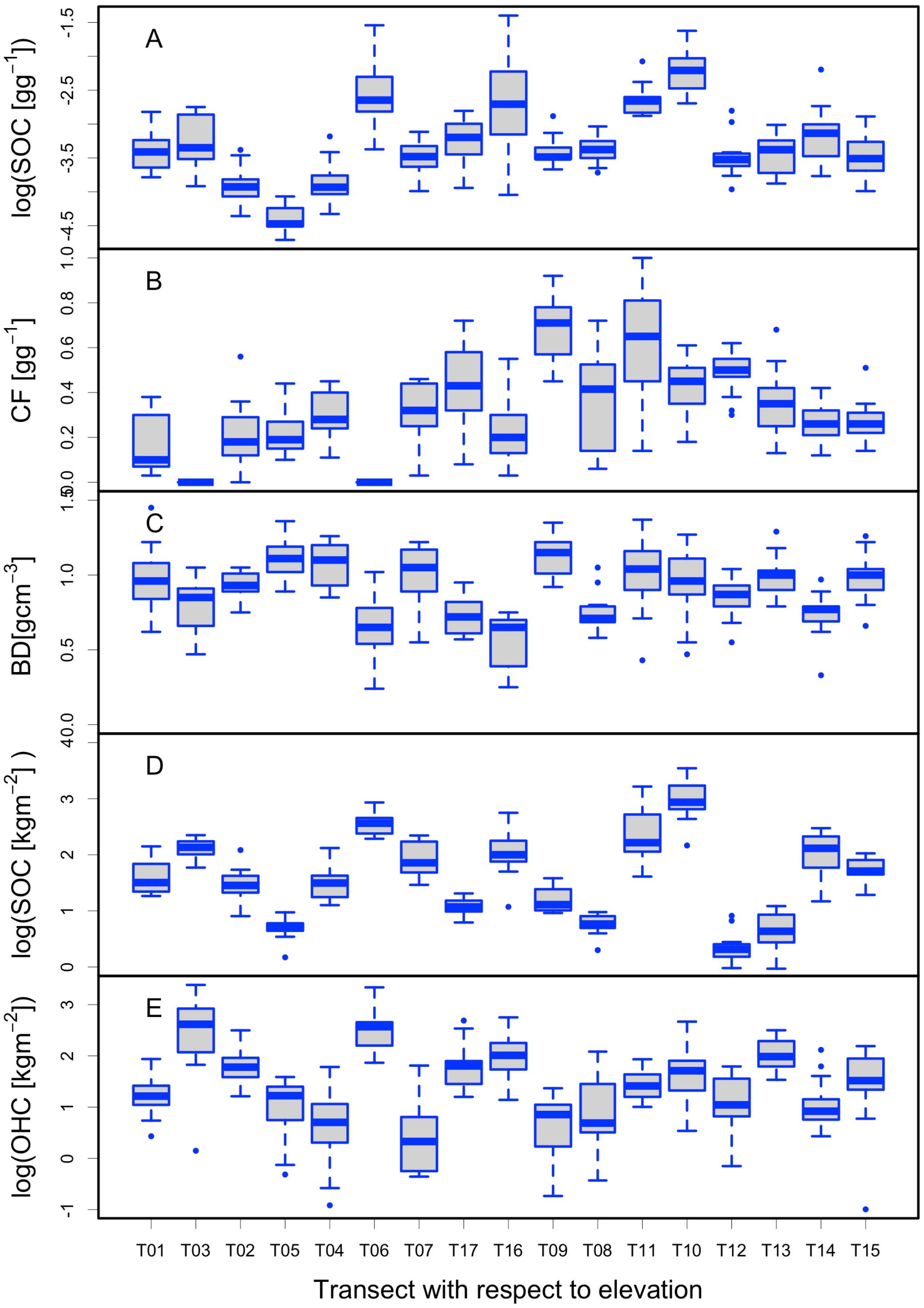


Figure 4.3: Boxplot representing the minimum, first, second (median) and third quantile and maximum of the A) SOC concentration log (SOC), B) coarse fraction (*CF*), C) bulk density (*BD*), SOC stock of D) the mineral soil log(SOC_{stock}) and E) of the organic horizon log(*OHC*) in each transect (T01 to T17). Boxplots represent all samples up to 30cm depth below the surface of a transect. The transects are ordered with respect to elevation from the lowest transect on the left and the highest transect on the right.

4.4.2 Relation between soil properties and site characteristics

The large variability of *SOC* concentration and SOC_{stock} suggests a major control of the site factors on soil organic carbon. Boxplots concerning the relationship between log (*SOC*), *CF*, *BD*, log (SOC_{stock}), log (OHC_{stock}) and soil-forming factors (elevation, slope, aspect, stand age of the forest, lithology and geomorphic environment) are given in Figure 4.4. The boxplots and calculated p-values of the Kruskal-Wallis test suggest that the soil properties are significantly different between the studied site characteristics (Figure 4.4).

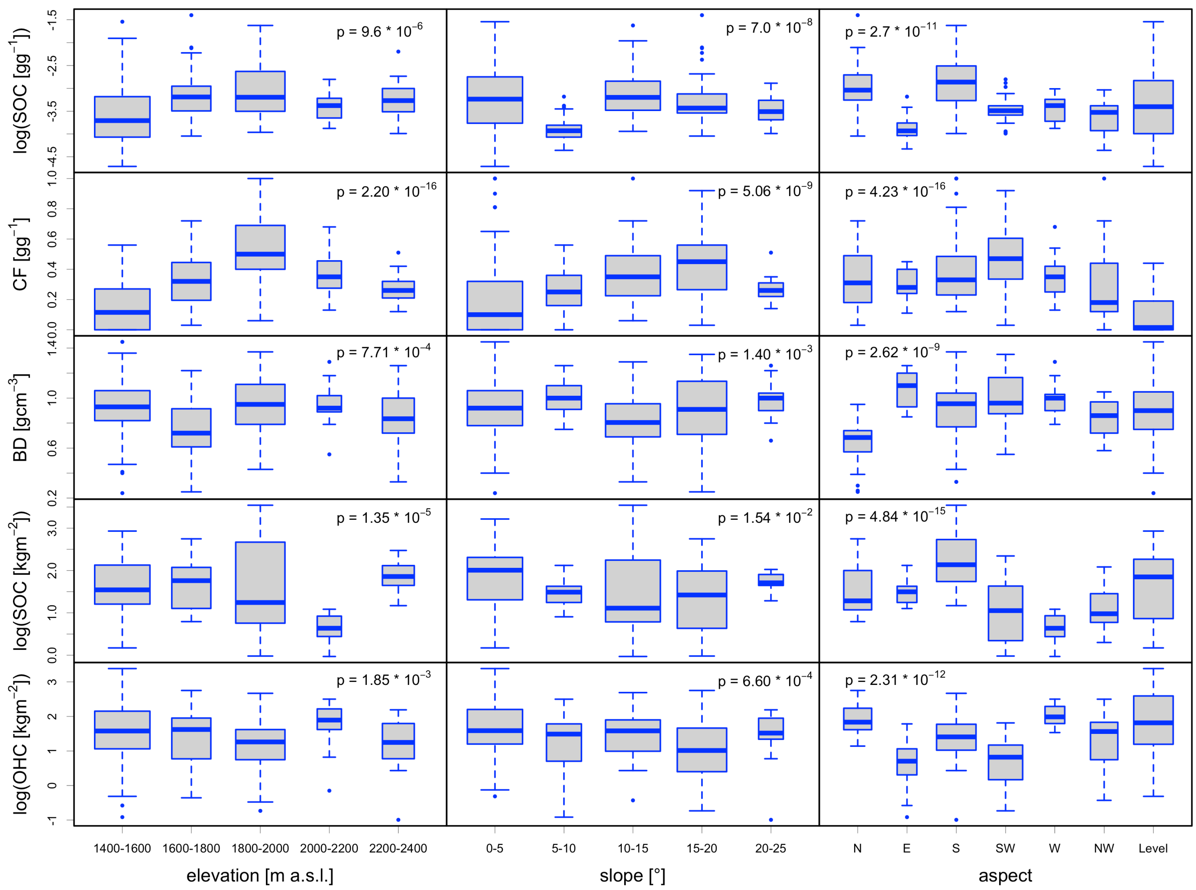


Figure 4.4a: Boxplots concerning the relationship between log (SOC), CF, BD, log(SOC_{stock}), log(*OHC*) and soil properties as well as soil forming factors: elevation, slope, aspect. p-values are derived using the Kruskal-Wallis test and give significant differences in the case of $p < 0.05$.

It is beyond the scope of this paper to discuss the relationship between soil properties and environmental characteristics in full detail. However we want exemplify some results. In general, it is obvious that there are generally no clear trends between SOC concentration, SOC stock, OHC stock and topographic indices such as elevation, slope and aspect. However, CF-values decrease with slope (Figure 4.4a) and with increasing sediment transport distant as expressed by the geomorphic environment at the transition from hillslopes to fan deposits and to floodplains (Figure 4.4b). The grain size sorting and increasing fine fraction suggest increasing SOC stocks with gentler slope positions and longer transport distance. However, more complex relationships with SOC concentration and bulk density blur these trends in terms of SOC stocks, which only increase slightly (and not statistically significant) with decreasing slope and increasing transport distance.

In terms of stand age, OHC stocks increase with forest age and remain constant with ages older than 1909 AD. In contrast, this relation is not seen in the mineral soil stocks. SOC stocks in stand ages older than 1866 AD are lower than those younger than 1866 AD.

In summary, single variables explain only small parts of the observed variability of the soil properties. In fact, the relationship with single variables seems to be distorted by the complex interaction between the environmental variables and the large spatial heterogeneity in mountain areas.

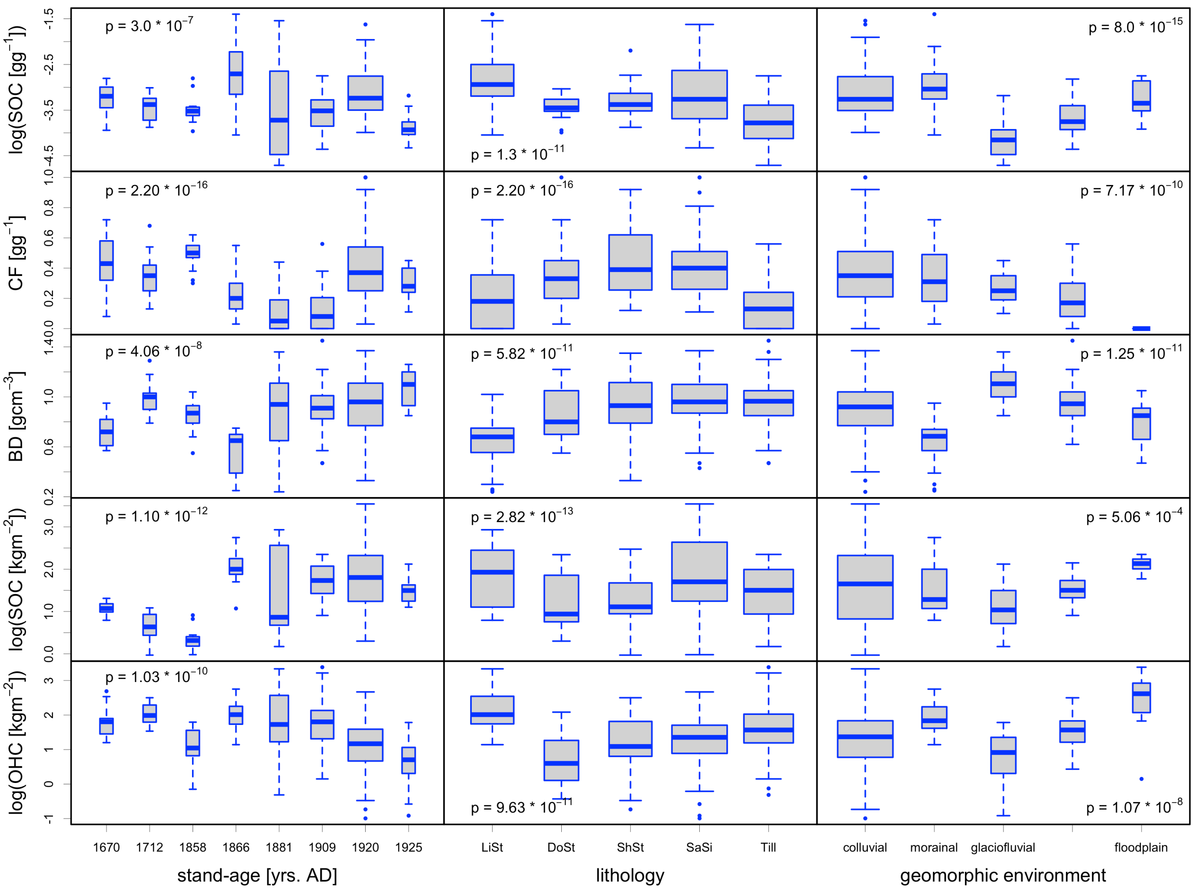


Figure 4.4b: (Boxplots concerning the relationship between log (SOC), CF, BD, log(SOC_{stock}), log(OHC) and soil properties as well as soil forming factors: stand age of the forest, lithology and geomorphic environment. p-values are derived using the Kruskal-Wallis test and give significant differences in the case of $p < 0.05$.

4.4.3 Analytical error and effects of spatial uncertainties on a SOC inventory

The results of the error calculation are given in form of the coefficient of variation *CV* [%], which is the ratio of the transect-averaged analytical errors (σ) or the standard deviation within each transect to the mean (μ) of each transect (Table 4.3). As described above, the analytical errors for *BD, CF* and SOC_{stock} are calculated based on the Gaussian error propagation (equation 4.4 and 4.5) using the analytical measurement errors of *ΔSOC*, *ΔCF*, *ΔBD* and *Δl*. In the case of the spatial uncertainty *ΔSOC*, *ΔCF*, *ΔBD* and *Δl* are given by the standard deviation within each transect. The spatial uncertainty of the SOC_{stock} is calculated based on the Gaussian error propagation (equation 4.5 and 4.6) and Taylor series expansion (equation 4.7). However, in this case *ΔSOC*, *ΔCF*, and *ΔBD* are given by the standard deviations within the transects. Main differences between the Gaussian error propagation and the Taylor series expansion result from the consideration of the co-variances in equation 4.7, which are neglected in equation 4.5.

Table 4.3: Analytical errors and spatial uncertainties of the studied soil properties given as the coefficient of variation (e.g. ratio of the standard deviation/analytical error and the mean value for each transect). Min, max und mean give minimum, maximum and mean values for the 17 transect.

soil property	analytical error [%]			spatial uncertainty [%]		
	min	max	mean	min	max	mean CV
SOC	10.0	10.0	10.0	26.3	76.4	40.1
CF	0.4	24.0	2.3	25.9	200	63.8
BD	9.3	10.6	10.0	14.9	42.6	23.5
l	10.0	10.0	10.0	0.0	0.0	0.0
$SOC_{stock\ Gauss}$	19.4	25	24.2	26.6	54.7	38.0
$SOC_{stock\ Taylor}$	-	-	-	9.2	115.5	40.8

Regarding the analytical errors, the largest uncertainty is given by the bulk density (10.0 %), followed by the assumed uncertainty of 10 % for SOC concentration and soil thickness. The analytical error of the coarse fraction is only 2.3 %. These uncertainties propagate to an uncertainty of the SOC_{stock} of 24.2 %. These values are significantly smaller than those of the spatial uncertainty calculated based on the Gaussian error propagation. The large standard deviation of the coarse fraction causes its largest spatial uncertainty of 63.8 % and thus introduces the largest uncertainty in the propagated mean error of the SOC_{stock} of 38 %. This value is directly comparable to the analytical uncertainty of 24.2 %. The mean spatial uncertainty of the SOC_{stock} calculated based on the Taylor series expansion is 40.8 %. Thus considering spatial co-variances between the factors that determine the SOC_{stock} increases the spatial uncertainty in this case only by about 2.8 %.

4.5 Discussion

In the following, the results will be discussed in terms of: i) the spatial variability of soil properties and SOC_{stock}, ii) the link of SOC stocks and site characteristics, and iii) the uncertainties associated with SOC inventories in these heterogeneous environments.

4.5.1 SOC stocks in mountain soils

The presented SOC concentrations, coarse fractions, bulk densities, and SOC stocks along an elevation gradient in the Canadian Rockies indicate a strong heterogeneity. Measured SOC stocks in the top 30 cm of mineral soil are on average 6.40 ± 5.58 kg C m^{-2} (ranging from 1.46 to 20.94 kg C m^{-2}) and present a slightly larger fraction of the stock compared to the organic horizon with a mean of 5.51 ± 4.70 kg C m^{-2} (ranging from 2.15 to 13.59 kg C m^{-2}).

Table 4.4 summarizes typical SOC stocks in mountain environments, which range between 2.94 and 22.8 kg C m^{-2}. Because the values are collected with different methods and for variable reference depths they can be compared in only the broadest sense. The data indicate, that our results are in the same order of magnitude to stocks measured in the upper 30 cm. Only, Genxu et al. (2002) demonstrated mean values of 9.81 kg C m^{-2} for the upper 30 cm of mineral soil at the Tibet Plateau, which are almost 30 % higher. Stocks calculated for the upper 1 m or to the bedrock interface even reach 22.8 kg C m^{-2} as demonstrated by Hitz et al. (2001) in mountain grasslands in Switzerland. These high numbers, however, need to be considered carefully because the given values do not represent mean stocks for a larger area but single point measurements. The value given by Garcia-Pausas et al. (2007) for the entire soil column of 15.3 kg C m^{-2} represent a more reliable upper limit of SOC stocks in mountain environments. SOC stocks of 3.1 kg C m^{-2} given by Ping et al. (2008) for mountain environments in the upper 1m of the North American Arctic are at the lower end of the tabulated values. Ping et al. (2008) attribute these low values to the high activity of erosion and slope processes, which effectively remove C from soils in the Arctic uplands.

A limited number of studies is available that estimate SOC stocks in mineral soils and in the organic horizon at once. As indicated by Ping et al. (2008) only a small fraction (generally less than 30 %) of OC is stored in the organic enriched surface layer in mountains (~0.7 kg C m^{-2}). The majority of OC is stored in the subsurface horizons and in the upper permafrost. In contrast to Ping et al. (2008), our values indicate that approximately the same amount of OC is stored in the organic horizon and the mineral soil. The larger fraction of OHC (compared to the SOC stock) is certainly due to the forest cover of our study site. Based on a global review, compiled by Vogt et al. (1986; 1995), OHC stocks in boreal forests range between 1.7 and 3.3 kg C m^{-2}, and are of similar order of magnitude to values given in this study (5.5 kg C m^{-2}).

Table 4.4: Global comparison of SOC stocks in different mountain environments.

Reference	Region	Environment	Elevation (masl)	# of samples	Reference depth (cm)	SOC_{stock} (kg C m^{-2})	OHC_{stock} (kg C m^{-2})
Grigal and Ohmann (1992)	Minnesota, Wisconsin, Michigan	Forest sites	no data	169	0.20	4.0	
Franzmeier et al. (1985)	North-central USA	forest, grasslands, cultivated lands	no data		0.20	4.7	
Homann et al. (1995)	western Oregon (USA)	Mountainous Forest sites	0-2040	499	0.20	6.3	
Yang, et al. (2008)	Tibetan grassland	Alpine steppe	2900 - 3500	810	0.30	2.94	
		Alpine meadow				6.17	
Genxu et al. (2002)	Tibet plateau	Alpine cold meadow	2900 - 3500	496	0.30	9.81	
Leifeld et al. (2005)	Switzerland	Mountain grasslands	2000 - 2500	544	1	6.29	
Jobbagy and Jackson (2000)	Cold temperate	Boreal forest	low	2700	1	9.30	
Van Miegroet et al. (2005)	Rockies, Utah	Meadow conifer ecotone	2600	120	1	10.90	
(Hitz et al., 2001)	Switzerland	Alpine grassland	2525		1	22.80	
Ping et al. (2008)	N-American Arctic region	Lowlands		139	1	40.0	15.1
		Uplands			1	33.2	7.5
		Rubblelands			1	2.6	0.8
		Mountains			1	3.1	0.7
Kopacek et al. (2004)	Tatra mountains	Meadow	1725 - 2370		to bedrock	8.40	
Garcia-Pausas et al. (2007)	Pyrenees	Mountain grasslands	2200		to bedrock	15.3	
This study	Canadian Rocky Mountains	Mountainous boreal forest	1585-3219	884	0.30	6.40	5.5

Differences regarding the methodology and reference depth may explain differences in the SOC stocks between the studies listed in Table 4.4. However, the major reason for the differences between mountain SOC stocks at the global scale can be sought in differences in the soil-forming factors including climate, parent material, topography, landscape position, vegetation, elevation, and (human) disturbance. The limited number of studies of mountain SOC stock and non-existent methodological standards with fixed conditions (same season, same depth, same blocks of land) currently prohibit quantifying the main controlling factors and the importance of mountain environments for the global carbon stock. Additionally, differences between values in Table 4.1 might be caused simply by chance as a result of the high spatial variability of the soil properties. This fact demands for the determination of the spatial variability and uncertainty of SOC stock, since only the study of Homann et al. (1995)

considers the spatial variability beyond the calculation of simple standard deviations. In any case, the relatively large SOC contents in the upper 30 cm indicate that soils in mountain environments comprise a very heterogeneous but significant global SOC pool, which is not sufficiently considered in large-scale SOC inventories.

4.5.2 Relation of SOC-related soil properties to environmental conditions

The relation of SOC concentration and stocks to environmental conditions are generally derived from small homogeneous (experimental) sites, in which only one single influencing variable is changed while others remain constant (e.g. Berhe et al., 2008; Yoo et al., 2006). This situation, however, does not represent the nature of mountain environments, in which environmental characteristics are strongly interlinked. Thus, findings obtained from experimental study sites are generally not applicable to larger, heterogeneous mountainous environments. This fact is demonstrated by the limited trends and the large scatter of the soil properties in relation to single environmental properties as given in Figures 4.4a and 4.4b. Each of the considered properties seems to have significant impact on the relevant soil properties (as suggested by the low p-values of the Kruskal-Wallis test), but expected relationships are mostly distorted by the interdependence of the environmental characteristic. Our results are in agreement with a study by Homann et al. (1995), in which regression analysis of 134 forest pedons in a largely forested, mountainous region in western Oregon indicated that combinations of site characteristics explained up to 50 % of the SOC variability. The large uncertainty therefore seems to be representative of mountainous environments with very heterogeneous relief and a small-scale variability of soil-forming factors, and are thus much higher compared to studies in environments with much lower topographic relief and intense human impact (e.g. Meersmans et al., 2008; Meersmans et al., 2009; van Wesemael et al., 2010).

4.5.3 Sources of uncertainty of soil organic carbon stocks

SOC inventories of the mineral soil generally require the determination of SOC concentration, bulk density, stone content, and soil depth (equation 4.2). Each property varies in space and its measurement is prone to analytical errors. This is especially true in mountain environments, which are characterized by strong gradients of the soil-forming factors such as topography, climate, and parent material. As indicated by our results, available regional datasets explained only some aspects of the spatial variability of soil properties, suggesting a large uncertainty in any inventorying effort. The spatial resolution of the regional datasets, which are used to explain the SOC inventory of the Kananaskis basin, is limited. Since the length of the measured transects (36 m) is similar to the resolution of the available data, environmental site characteristics are assumed to be constant for each transect. Thus, the limited predictive power of these dataset for SOC stock and relevant soil properties may be attributed to the following sources of uncertainty: i) exclusion of important site characteristics, and uncertainty regarding their relation to SOC stocks, ii) spatial variability of soil properties within individual transects, and iii) analytical errors associated with measurement of the soil properties.

Important site characteristics that control soil formation and SOC are considered to be climate (esp. temperature and precipitation), vegetation (e.g. type, structure, and stand age), topography (altitude, aspect, slope, landscape position, and micro-topography), and geology/geomorphology (controlling characteristics of the parent material and hydrology). A detailed description of all site characteristics requires a process-based knowledge of the effect of these characteristics on SOC, which is currently not available. Furthermore, available data do not represent the necessary site characteristics. For example, the geological map or the terrain inventory do not represent the grain size of the parent material, but integrate more general geological and geomorphological characteristics. Thus, soil-forming processes and properties need to be approximated based on available data, without precise knowledge of the link between available data and the desired parameter.

Second, uncertainties associated with the spatial variability of soil properties within individual transects and the errors associated with the analytical precision were evaluated based on the Gaussian error propagation and the Taylor series expansion (Table 4.3). For all studied soil properties, the uncertainty associated with spatial variability of the soil properties within the transects is larger than the uncertainty associated with the analytical precision. This is especially true for the coarse fraction, which introduces the largest spatial uncertainty (mean CV = 64 % and maximum CV up to 200 %) in this analysis. In the Kananaskis area, the coefficients of variability of SOC concentration and bulk density are 40 % and 23 % respectively and are thus of secondary importance. The large spatial variability of the coarse fraction is in good agreement with results presented by Schrumpf et al. (2011), who suggested that bulk density and coarse fraction are highly variable in the upper soil layers of cropland and in stone-rich soils. In contrast, Don et al. (2007) observed higher relative variability of SOC concentration than of bulk densities at two grassland sites in Germany. Goidts et al. (2009) found that SOC concentrations and stone contents (e.g. coarse fraction) were usually more important than bulk density in Belgian grassland and cropland sites. The differences between Don et al.'s (2007) results and our study might be influenced by the high stone content of mountainous soils in comparison to their studied grassland sites.

The comparison between the coefficient of variation of the SOC stock based on the Gaussian error propagation (38 %) and the Taylor series expansion (41 %) shows that spatial co-variances between the soil properties, which determine SOC_{stock} (equation 4.2), introduce an additional, but small source of uncertainty (Table 4.3). Uncertainties derived from the Taylor series expansion, which considers co-variances between soil properties, are generally higher than those calculated based on the Gaussian error propagation, which does not take such co-variances into account. Differences between the Gaussian error propagation and the Taylor series expansion might strongly increase in the case of strong correlations between the soil properties, which determine the SOC stock (equation 4.2). The estimated coefficients of variation of the SOC stock calculated based on the Taylor series expansion (41 %) are directly comparable to results presented by Goidts et al. (2009), who presented values for grasslands and croplands in Belgium, which are characterized by strong human impact, humid climatic conditions, and a gentle topography. However, their estimates ranged between 5 % and 35 % and are thus smaller than the 41 % *CV* of the SOC_{stock} in the Kananaskis mountainous environment. In general, the applied nested sampling approach combines high-resolution sampling of the site-scale variability and of large-scale SOC differences, drive by changing environment conditions. The approach provided promising results for the analysis of the sources of uncertainties for larger scale SOC stocks in complex terrain.

4.5.4 Implications for regional SOC inventories

To summarize, our results suggest that analytical uncertainties of SOC inventories in subalpine environments are of secondary importance. The main source of uncertainty is introduced through the large spatial variability of relevant soil properties in mountain environments. This is especially true for the coarse fraction of mountain soils, which shows the largest coefficient of variation. The large variability of the sediment texture (and thus the coarse fraction) in the study areas is conditioned by the bedrock and modified by erosional and depositional processes (Jackson, 1987). This fact is shown by our data through the rather high correlation of the coarse fraction with lithology and the correlation of lithology and geomorphology with *SOC* and *BD*. Lithology and geomorphology provide key information to reduce the uncertainty of the regional SOC inventory. Therefore, a better representation of the local variability for regional inventories might be achieved through the analysis of the frequency distributions stratified by lithology and geomorphology rather than the simple mean or median values of the considered soil property in each lithological or geomorphological unit.

The frequency distributions of CF stratified by lithology (Figure 4.5 left) and geomorphology (Figure 4.5 right) support this statement. The CF distribution differs on the one hand between positively skewed distributions of limestone and till and symmetrical distributions of sand and shale stones and on the other hand between different geomorphic environments; while colluvial deposits show a more or less symmetrical distribution, tills and alluvial fan deposits are positively skewed. Overbank deposits in floodplains exhibit only a small variability with low CF values. The studied distributions are in good agreement with the geological and geomorphological knowledge on the weathering of bedrock and the sorting mechanisms through different geomorphological processes in mountain environments. In general, we state that the detailed study of the CF distributions in different lithological and geomorphological units may help to be better represent the observed local variability and therefore reduce the uncertainty associated with regional SOC inventories.

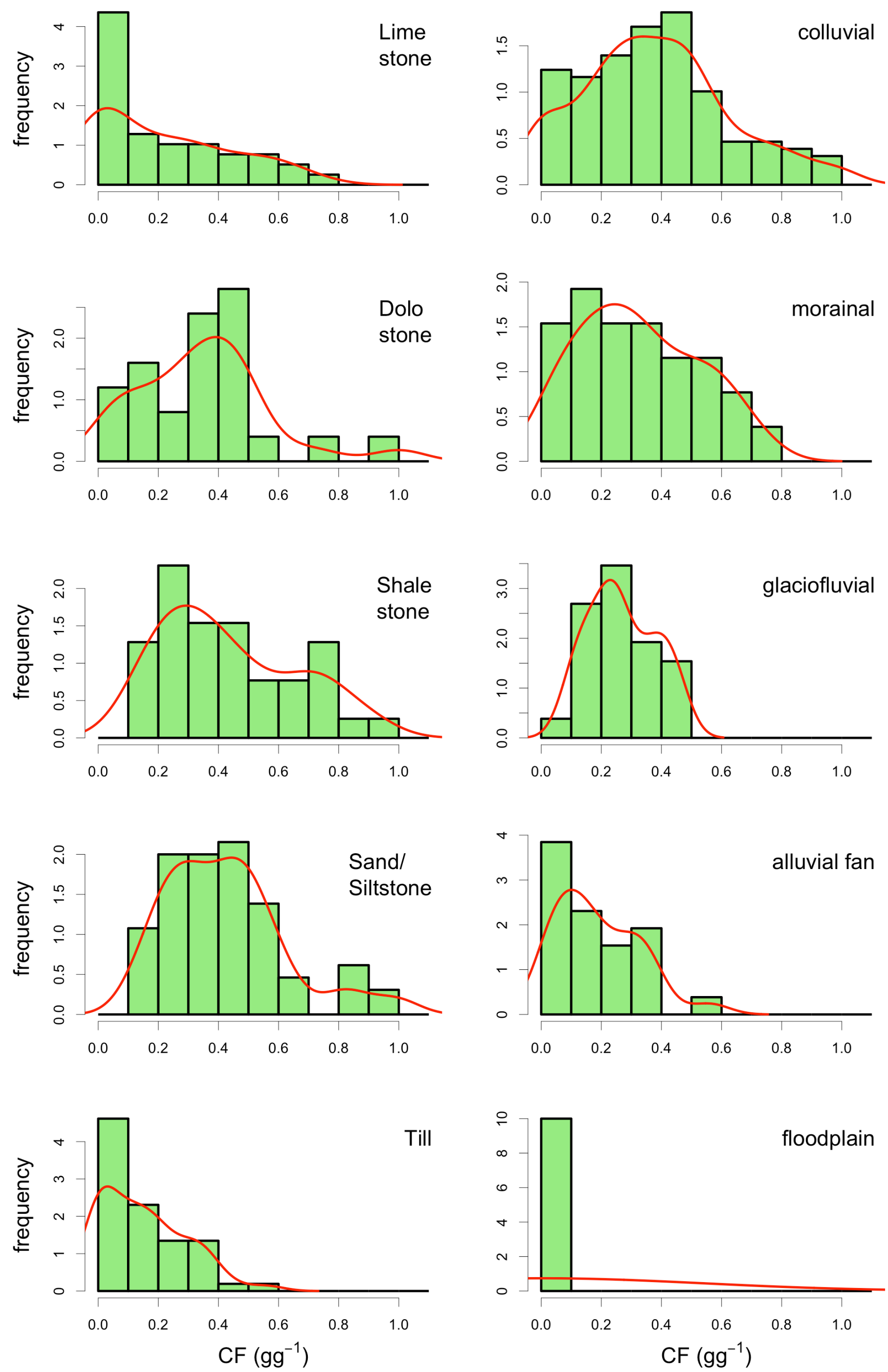


Figure 4.5: Distribution of coarse fraction (*CF*) stratified based on the lithology (Limestone, Shalestone, Dolostone, Sand-Siltstone, Till) and the geomorphic environment (colluvial, morainal, glaciofluvial, alluvial and floodplain).

The implementation of these distributions remains a future research task, and will not be conducted in this study. However, the results of the uncertainty analysis have major implications for choosing the appropriate sampling strategy to calculate SOC inventories. Soil properties with large spatial variability need a large number of spatially distributed measurements, while soil properties characterized by large analytical errors require high quality but low quantity measurements. In our case, the large coefficient of variation of the coarse fraction and SOC contents suggests that a large number of spatially distributed measurements are needed. An effective sampling strategy therefore should focus on the spatial distribution and a large number of measurements, while the analytical precision of these measurements is of secondary importance. Since the variability of the coarse fraction is mainly controlled through small-scale variability of geomorphic processes, we state that SOC inventories in mountain environments require a detailed understanding of the condition of the spatial distribution of sediment transport and accumulation processes.

The applied nested sampling strategy provides a very good tool to establish the site scale variability in heterogeneous environments, which has been insufficiently considered. To evaluate the sources of uncertainty in mountain environments, more systematic studies with a focus on site-scale variability and large spatial patterns need to be obtained.

4.6 Conclusion

Based on the main objectives of this paper, the following conclusions can be derived for the compilation of SOC inventories in subalpine environments:

First, measured soil properties (e.g. SOC concentration, bulk density, coarse fraction, and soil thickness) and calculated SOC stocks in the Kananaskis basin indicate a large variability of environmental conditions that govern SOC inventories in the mountainous environment. The large variability is especially associated with large variation of the coarse fraction, SOC concentration and calculated SOC stocks.

Second, the large variability is presented by low predicting power of the site characteristics (extracted from available data such as DEM, geological and terrain inventory map) and SOC stocks. The findings suggest a complex interaction of SOC stocks and environmental conditions in mountain environments and demand consideration of the whole set of available data when establishing SOC inventories.

Third, the applied nested sampling strategy, which was designed to represent the spatial resolution of the available data on the one hand and to estimate the site-scale variability of soil properties and SOC stocks on the other, provided useful insights to evaluate the analytical and spatial uncertainty of SOC inventories in mountain environments. The spatial uncertainty of the SOC stock, which is associated with the variability and co-variance of soil properties within the transects, represents approximately 41 %. The largest spatial uncertainty in our study site is introduced through the large variability of the coarse fraction. The spatial uncertainty is generally twice as large as errors associated with the sampling and laboratory analysis to estimate soil properties and SOC stock. Thus, to reduce the uncertainty of SOC inventories in mountain environments, our results demand a better representation of the complex interaction of small-scale variables involved in SOC stock variability and soil-forming properties and processes. This will be mainly achieved through a larger number of measurements and a better representation of geomorphic processes that introduces a high degree of spatial variability of SOC-relevant soil properties in mountain environments.

Acknowledgement

We thank the Biogeoscience Institute of the University of Calgary for logistic and lab support at the Barrier Lake field station. A Doctoral Student Research Award supported this work. We owe gratitude to the “Department of Foreign Affairs and International Trade Canada” who rendered this field study possible. We thank two anonymous reviewers for their helpful comments on the manuscript.

5. Spatial variability of soil organic carbon stocks in an alpine setting (Grindelwald, Switzerland)

Hoffmann, U., Jurasinski, G., Hoffmann, T., Kuhn, N. J. (in prep.): Spatial variability of soil organic carbon stocks in an alpine setting (Grindelwald, Switzerland).

Abstract

Mountain environments represent heterogeneous environments with shallow soils that are sensitive to human impact and climate change. Despite the thin soil cover, high soil organic carbon content of mountain soils may provide a major source of atmospheric CO_2, if released. However, the importance of mountain soils remains controversial, largely due to insufficient information on the spatial variability of mountain SOC stocks. Here, we study the spatial variability of soil properties and SOC stocks in a changing mountain environment in the Bernese Alps (Switzerland). We use different interpolation techniques and analyze the sources of uncertainty using a nested sampling approach and the Gaussian error propagation.

We found no major differences in the average SOC stocks of the study area, the general patterns of the predicted stocks and the explanatory power of the different models. However, the small-scale variation varies considerably depending on the employed interpolation technique. This indicates that spatially averaged SOC stocks in mountain environments do not only require a high sampling density of soil measurements. Further, a high spatial density is required to understand the factors that control the variability within the study site. This is especially true for the coarse fraction, which introduces the largest source of uncertainty. Nested sampling designs seem to provide an efficient tool to study SOC inventories and their associated sources of uncertainties in mountain environments.

5.1 Introduction

Soil organic carbon (SOC) plays a key role in the global carbon (C) cycle and soils are an important C reservoir. Worldwide, SOC storage in surface soils has been estimated to 2011 Gt C and is almost twice as large as the atmospheric C-pool (Bolin and Sukumar, 2000 ; Perruchoud et al., 2000; Sedjo, 1992). Small changes in the SOC pool therefore can have large implications for atmospheric CO_2-concentrations. The detailed knowledge of the spatial distribution of SOC and the feedbacks between SOC, soil forming processes and environmental conditions (such as climate and land use) is important (Simó et al., 2010) for climate modeling. A large number of regional SOC inventories have been compiled to establish the relationship between environmental conditions and SOC stocks (Ganuza, 2003; Homann et al., 1995; Martin, 2011). Generally, these inventories rely on relationships between SOC and environmental conditions, which are derived from regional datasets, such as elevation and temperature (Garcia-Pausas, 2008), soil, bedrock material and texture (Banfield et al., 2002; Brady and Weil, 2002; Hoffmann et al., 2009), pH (Falloon and Smith, 2009; Heckman et al., 2009), topography (Berhe et al., 2008; Prichard et al., 2000; Yoo et al., 2006), vegetation and stand age of the forest (Luyssaert et al., 2008; Zhou et al., 2006) and disturbance due to human activity (Czimczik et al., 2005; Morgan et al., 2010). For instance, Leifeld et al. (2005) quantified current SOC stocks in agricultural soils in Switzerland using land use, soil characteristics (e.g. clay content) and altitude. Their results suggest that 16 %

of the national SOC stock has been lost due to historical land use changes in the cultivated areas. Similar results have been found using SOC inventories in North America (Lacelle et al., 1997), in different European countries (Arrouays and Pelissier, 1994; Batjes, 1996; Goidts and van Wesemael, 2007; Krogh et al., 2003), or in China (Wu et al., 2003).

SOC inventories are characterized by large uncertainties that may result from: i) the large spatial variability of soil properties (such as grain size, bulk density, soil thickness and SOC concentration) and the resulting SOC stock (Don et al., 2011; Don et al., 2007), ii) the imperfect knowledge between environmental conditions and SOC stocks, and iii) the limitations of regional datasets (such as geological and soil maps) to represent the small scale variability of soil properties (Homann et al., 1995). This is especially true in mountain environments, which are characterized by a greater geodiversity than any other landscapes (Slaymaker et al., 2009). While elevation and thus temperature differences are identified as the dominant controls on mountain SOC at regional scales (Djukic et al., 2010; Leifeld et al., 2005; Van Miegroet et al., 2005; Van Miegroet et al., 2007), microtopography (e.g. slope curvature and aspect (Egli et al., 2009; Tan et al., 2004), soil properties (e.g. soil type, soil moisture, pH and clay-content (Djukic et al., 2010; Leifeld et al., 2005) and vegetation (e.g. type and stand age (Luyssaert et al., 2008; Zhou et al., 2006) may introduce a large variability of mountain SOC at local scales. Small-scale variability may even impose strong scatter at large-scales and conceal relationships between SOC, topography and climate. For instance, Homann et al. (1995) found that only 50 % of the observed SOC variability in mineral soil could be explained by multiple regressions of SOC stocks against regional data in a study on the largely forested mountainous region of Western Oregon. Without full understanding of the interplay of factors controlling SOC on different spatial and temporal scales, predictions of the response of SOC to global warming are difficult. In this respect special attention should be given to mountain regions, which i) show a high sensitivity regarding environmental changes, ii) represent major methodical challenges for the compilation of adequate SOC inventories and iii) lack a reliable number of comparable SOC inventories (Stutter et al., 2009; Theurillat et al., 1998) because the majority of SOC studies focused on agricultural lowlands or arctic peatlands (Burnham et al., 2010; Ping et al., 2008; Vardy et al., 2000).

The available studies on SOC stocks in mountain environments (Hitz, 2002; Stutter et al., 2009; Theurillat et al., 1998) show that major questions remain regarding i) the relationship between regional datasets of topography, land-use, soil generation, lithology and SOC stocks, ii) the identification of factors that significantly contribute to the uncertainty of SOC stocks and iii) the optimal spatial interpolation methods to estimate the target variable at unvisited locations for the assessment of SOC stocks in changing mountain environments.

Here we investigate the variability of SOC in a heterogeneous mountain environment in the Swiss Alps (Grindelwald), which is strongly modified by human land use since several hundred years. The objectives of our study are i) to test the applicability of regional datasets to establish mountain SOC stocks, ii) to identify and quantify the main sources of uncertainty in regional mountain SOC stock inventories and iii) to develop a methodological framework for spatial prediction based on different interpolation methods to assess the accuracy of spatial prediction with different sampling sizes.

5.2 Study site

The study area is located in the Lütschine Valley within the Bernese Alps (Canton of Bern, Switzerland). The southern border of the study area is located in front of the prominent Alpine landscape that features the Wetterhorn, Eiger, Mönch and Jungfrau mountains. The study site is placed between the Wärgistal torrent (northern boundary), the Eiger Northwall and the Sandbach in the South. The western boundary is the ridge of the Kleine Scheidegg (2061 m a.s.l.) and the eastern boundary is given by the Schwarze Lütschine in Grindelwald Grund (796 m a.s.l.). The study site covers an area of 8.6 km² (Figure 5.1).

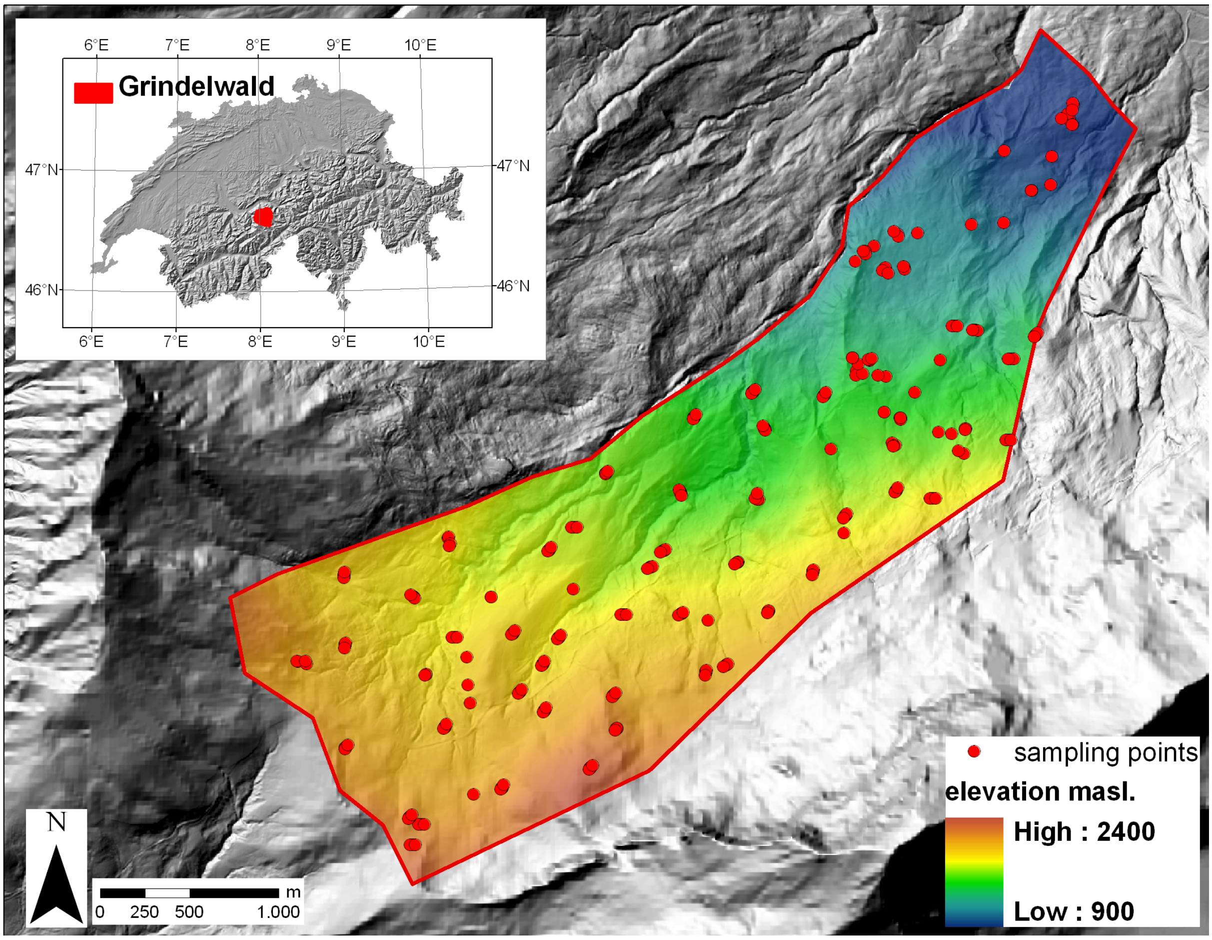


Figure 5.1: Location of the Grindelwald area within the Swiss Alps (inset) and elevation with shaded relief and location of the sampling points within the study site.

The morphological formation of the study area is dominated by the lithostratigraphic units of the crystalline Aarmassive (Labhart, 2005). The imposing limestone walls of the Eiger, which forms the southern border of the flysch and molasse basin of Grindelwald, characterize the geology of the study site. Schist characterizes the common bedrock material between Kleine Scheidegg and Grosse Scheidegg. These schists are highly erodible and the low permeability forms a very soft relief. This material is characterized by high soil moistures and prone to recent landslide activity. In contrast to the schist, the iron-sandstone is highly permeable, providing a large fraction of coarse debris and a high activity of debris flows. The relief of the iron sandstone is mainly formed by glacial erosion and deposition during the Pleistocene.

The climate is subalpine to alpine with perennial snow cover on the tops of the mountains and can be described as cool and moderately humid at lower altitudes, where the mean annual temperature is 5.9 °C (in Grindelwald), while mean annual precipitation ranges from 1300 mm (in Grindelwald) to 3000 mm at higher elevations (e.g. Große Scheidegg).

Grindelwald valley has a diverse mosaic of forest, pasture and cultivated fields. The potential timberline is at approximately 1673 m a.s.l. (Bundesamt für Geoinformation, 2005). The vegetation of the valley comprises fertilized pastures and meadows, natural alpine grassland, arolla pine forest, spruce forest, moorlands, decidous forest, semi-dry grassland and riverine forest. The agriculturally used areas range from 700 m to 2500 m above sea level and are mainly used for animal husbandry well adapted to the natural conditions. Up to 1400 m a.s.l., the land is used mainly as pastures, which are mowed three times the year in addition to spring and autumn pasture farming. The mountain pasture above 1400 m a.s.l. is exclusively pasture land. On extensively used mountain pastures particular dwarf shrub vegetation developed.

In general the study area is characterized by pedological distinctions between contrasting parent materials and between altitudinal belts. On till deposits the soil formation in the valley bottoms is characterized by neutral to weakly acidic cambisols, in the higher regions the cambisols are rich in humus. On carbonate talus deposits with grassland and forest carbonate rich to neutral regosols are dominant. On talus deposits with low vegetation cover humus rich rendzinas (FAP, 1985) prevail.

5.3 Materials and methods

5.3.1 Sampling strategy

Soil sampling was conducted on 403 sampling sites during two field campaigns in July 2008 and 2009 using a two-level stratified nested sampling approach (Stutter et al., 2009; Zhang and McGrath, 2004). Nested sampling approaches have the clear advantage to analyze the spatial variability of the soil properties at different spatial scales and to evaluate the impact of small scale variability on the larger scale.

To analyze the large scale variability within the study site, we have calculated the sampling sites to represent the aerial frequency distributions of the considered environmental variables as given by the regional datasets. Available regional datasets in our study area included a digital elevation model (DEM) with a 10 m grid resolution, the areal statistics of Switzerland, which indicates the dominant land cover type for 100*100 m grid cells, the soil map of the Grindelwald area (scale 1:25000) and the geological map (scale 1:25000). The DEM and the aerial statistics were provided by the Amt für Geoinformation of the Canton Bern. Topographical parameters (such as elevation, slope, aspect and curvature) were extracted from the 10 m-DEM based on standard ESRI-ArcGIS algorithms.

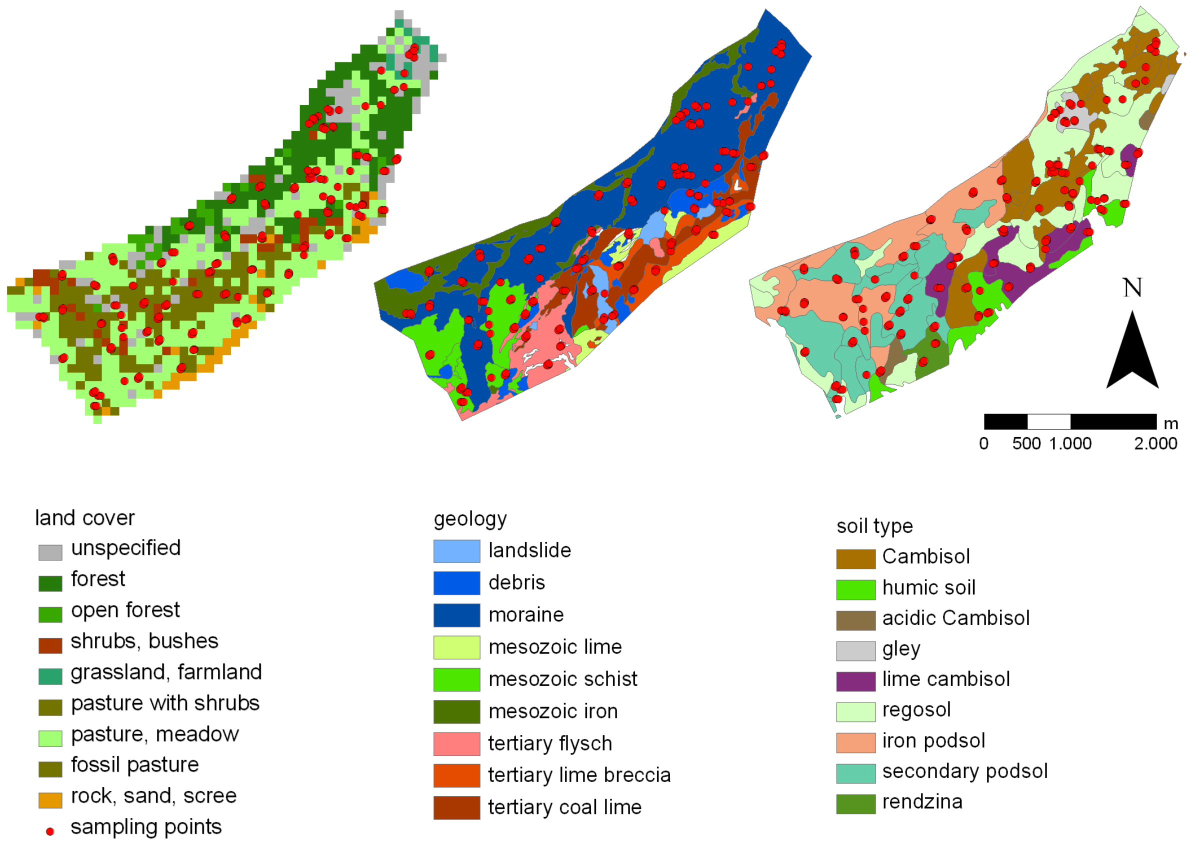


Figure 5.2: Land-cover, geology and soil type in the study site.

We further estimated land coverage of each sampling site in the field for additional ground truthing and to evaluate land coverage presented in the areal statistics. Lithology and land use was stratified into nine and eight classes, respectively (see Table 5.1 for considered classes and abbreviations). The available soil map gives information on soil types and the grain size index (GSI). The GSI represents the dominant coarse fraction and clay content of the mapped soil units (Table 5.1 and Figure 5.2).

The small-scale variability at each sampling site was quantified along several 30 m long transects oriented parallel to the slope with a primary core (PC) in the center and six secondary cores (SC) to each side of the PC. The SC were placed at logarithmic distance increments to the left (e.g. -10 m, -2.5 m, -1 m, -0.25 m) and right (+0.5 m, +1.5 m, +5 m, +20 m) of the PC (Simbahan and Dobermann, 2006; Simbahan et al., 2006). The length of the transects (30 m) was chosen to resemble the resolution of the used regional proxy data. Thus, the variation within the transects is not explained by these regional proxy data and is assumed to be related to the spatial uncertainty. Therefore, we assumed that the transects have homogenous characteristics according to the regional dataset and that the variability of the soil characteristics within them is not represented by the regional dataset. We thus refer this regionally "unexplained" variability to the spatial uncertainty.

At each PC an excavation pit was dug through the entire soil column. The soil was sampled every 5 cm in the upper 20 cm of the soil column. Below 20 cm depth we took samples every 20 cm until the bedrock was reached. We described the profile in detail following BKA 5 (AG Bodenkunde 2005) including field estimates of soil type, texture, color, and moisture. At the SCs sampling was generally limited to the upper 10 cm and the samples were only analyzed for SOC concentration (SOC), bulk density (BD) and the coarse fraction (CF).

Table 5.1: Abbreviations (as used in Figure 5.4), number of samples and short description of each class of the categorical datasets (geology, soil type, grain-size index and land use).

Abbrevia-tion	No. of samples	description		Abbrevia-tion	No. of samples	description
Geology				**Soil type**		
1	42	tertiary flysch		E	9	acidic Cambisol
3	52	mesozoic schist		Q	113	secondary podsol
11	12	mesozoic lime		U	16	rendzina
2	35	mesozoic iron		P	62	iron podsol
8	167	moraine		O	80	regosol
4	54	debris		B	53	cambisol
6	63	tertiary coal lime		K	81	lime cambisol
9	18	tertiary lime breccia		C	27	humic soil
7	9	landslide		G	11	gley
Grain-size-index (GSI)				**Land-use**		
4	129	skeleton/sandy (<20% clay)		99	7	rock, sand, scree
5	10	skeleton/loamy (20-30% clay)		88	218	pasture, meadow
8	9	skeleton/sandy/loamy (< 30% clay)		11	72	forest
2	95	minor Skeleton/loamy (20-30% clay)		86	55	pasture with shrubs
1	58	minor skeleton/sandy (<20% clay)		82	9	grassland, farmland
3	72	minor skeleton/ silty/clayey (>30% clay)		16	21	shrubs, bushes
6	54	skeleton/silty (<30% clay)		89	26	fossil pasture
7	25	skeleton/clayey (>30% clay)		12	27	open forest

5.3.2 Soil analyses

Mineral soil samples were taken using a soil core (cylinder) with a diameter and height of 5 cm (98.2 cm^3), which allowed the estimation of the soil bulk density [g cm^{-3}] based on the total soil weight [g] and the volume of the cylinder (Ravindranath and Ostwald, 2008; Rodeghiero et al., 2009; Schrumpf et al., 2011). All soil samples were oven-dried at a temperature of 105 °C and weighted. Afterwards mineral soil samples were sieved (< 2 mm) to remove roots and rock fragments and to determine the weight of the coarse and fine fraction. For PCs, the fraction <0.032 mm was subject to further particle size analyses carried out with a SediGraph (SediGraph 5100, micromeritics); we especially focused on the clay fraction, which generally provides the strongest relationship to the SOC in mineral soils (Lal, 2005a; Leifeld et al., 2005; Tan et al., 2004).

SOC was determined with a LECO analyzer (RC-612) based on a thermoanalytical analysis, which differentiates between the organic (SOC) and inorganic (SIC) carbon fractions by the specific temperature at which they oxidize. The release of organic carbon was measured at a constant temperature of 550° C. After the CO_2 concentrations droped to <1 % of the peak intensity, the sample was further heated up to 950° C at a rate of 120° C per minute to measure the release of the inorganic fraction (RC612, 2006). SOC concentrations were then estimated through the time-integrated CO_2 concentrations.

5.3.3 Calculation of SOC stock

For each representative layer i of a soil sample with thickness l_l [cm], $SOC_{stock,i}$ [kg C m^{-2}] was estimated based on equation 5.1 (Schrumpf et al., 2011):

$$SOC_{stock,i} = 0.1 \times l_i \times BD_i \times SOC_i \times (1\text{-}CF_i / 100) \qquad \text{(equation 5.1)}$$

with SOC_i the total organic carbon concentration [g g^{-1}]; CF_i the coarse fraction (fraction > 2 mm) [g g^{-1}]; BD_i the soil bulk density [g cm^{-3}]; l_i the thickness of representative sampling horizon [cm]. SOC stocks (SOC_{stock}) per sampling site where calculated by summarizing the $SOC_{stock,i}$ of each layer i at the corresponding sampling site (Ellert et al., 2002; Grossmann et al., 2001 ; Wang et al., 2004):

$$SOC_{stock} = \sum SOC_{stock,i.} \qquad \text{(equation 5.2)}$$

For the PCs, SOC stocks were calculated for each 10 cm, down to the base of the soil column (e.g. $SOC_{stock,10cm}$, $SOC_{stock,20cm}$, $SOC_{stock,30cm}$). SOC stocks at the SCs were only calculated for the upper 10 cm of the mineral soil and extrapolated to 30 cm based on the ratio $SOC_{stock,30cm} / SOC_{stock,10cm}$ at the PCs. The reference depth considered in this work is 30 cm in agreement with European standards (Jones et al., 2004).

5.3.4 Spatial variability

We used multiple analyses of variance (ANOVA) to test the relationship between SOC stock and environmental site characteristics. F and p values were calculated in both cases to test the model's ability to explain the variation of the data and its population, as well as to test the significance of the relationship (Table 5.3). Furthermore SOC stock was plotted as a function of topographic parameters (elevation, plan curvature, profile curvature and slope) and boxplots were derived for soil forming factors (lithology, soil type, grain-size index and land-use) to represent the relationships between SOC stock and soil properties (Figure 5.4).

5.3.5 Evaluation of uncertainties

The calculation of SOC stocks relies on the measurement of total organic carbon concentration, coarse fraction, bulk density and thickness of representative sampling horizon (equation 5.2). Each of these parameters is associated with measurement errors and spatial variability that are propagated during the calculation of the SOC stock (Freibauer et al., 2004; Meersmans et al., 2008).

The uncertainty of SOC concentrations (ΔSOC) is given by the precision of the RC 612 and is assumed to be 10 % (RC612, 2006). This is in agreement with replicated measurements of the same soil sample. Similarly, the uncertainty of the layer thickness *Δl* of the samples is based on replicate measurements of selected samples and is defined to be 10 % as well. The uncertainties of the coarse fraction and the bulk density (*ΔCF* and *ΔBD)* are calculated based on the Gaussian error propagation (Taylor, 1997):

$$\Delta BD = \sqrt{\left(\frac{\Delta f_t}{V}\right)^2 + \left(\frac{f_t}{V^2}\Delta V\right)^2} \quad \text{and} \quad \Delta CF = \sqrt{\left(\frac{\Delta f_g}{f_t}\right)^2 + \left(\frac{f_g}{f_t^2}\Delta f_t\right)^2} \qquad \text{(equation 5.3)}$$

with f_t and f_g the weight of the total soil sample and the coarse fraction, respectively, and Δf_g und Δs_g analytical uncertainties of f_t and f_g, which are given by the precision of the balance (±0.1 g). Likewise the uncertainty of the volume V of the sampling cylinder is assumed to be ΔV = 10 %.

To evaluate the analytical uncertainty of the SOC stock (ΔSOC_{stock}) we used the Gaussian error propagation (equation 5.3), which is based on the uncertainties of the SOC concentration (*ΔSOC*), the coarse fraction (*ΔCF*), the bulk density (*ΔBD*) and layer thickness (*Δl*):

$$\Delta SOC_{stock,i} = (T_1^2 + T_1^2 + T_1^2 + T_1^2)^{1/2} \quad \textit{and} \quad \Delta SOC_{stock} = \sum \Delta SOC_{stock,I} \qquad \text{(equation 5.4)}$$

with T_1 to T_4 the individual contributions of *ΔSOC*, *ΔCF*, *ΔBD* and *Δl* to the total uncertainty of the SOC_{stock} calculated according to equations 5.5:

$$\text{T1:} \quad \frac{\partial SOC_{stock}}{\partial SOC}\Delta SOC = (1-CF)\cdot BD\cdot l\cdot \Delta SOC$$

$$\text{T2:} \quad \frac{\partial SOC_{stock}}{\partial CF}\Delta CF = SOC\cdot BD\cdot l\cdot \Delta CF$$

$$\text{T3:} \quad \frac{\partial SOC_{stock}}{\partial BD}\Delta BD = SOC\cdot (1-CF)\cdot l\cdot \Delta BD$$

$$\text{T4:} \quad \frac{\partial SOC_{stock}}{\partial l}\Delta l = SOC\cdot (1-CF)\cdot BD\cdot \Delta l$$

(equation 5.5)

The second source of uncertainty arises from our imperfect knowledge and the small-scale variability of soil forming processes and the inability of regional proxy data (such as geological and soil maps or digital elevation models) to represent the small-scale variability because of their limited resolution. The summarized effects of the unexplained spatial variability are given by the standard deviation of the relevant soil properties (e.g. SOC concentration, bulk density and coarse fraction) within each transect.

We calculated the propagation of the spatial uncertainties for the resulting SOC stocks with two different approaches. The first approach relies on the Gaussian error propagation (equations 6.4 - 6.6) and thus resembles the calculation of the analytical uncertainties; but instead to the calculation of the analytical errors, *ΔSOC*, *ΔCF*, *ΔBD* and *Δl* are given by the standard deviations within each transect. Since the same equations are used to estimate the propagated analytical and spatial uncertainty ΔSOC_{stock} they are directly comparable to each other. This allowed us to independently evaluate the contribution of the analytical and spatial uncertainties. However, the application of the Gaussian error propagation is limited since it does not take into account the co-variances of the input parameters of equation 5.1, which may decrease or increase SOC stocks and should therefore be estimated (Dileep et al., 2008). Therefore, we used a second approach that is based on the linear Taylor series expansion (Lo, 2005; Moelders et al., 2005) and has recently been applied to evaluate the uncertainties of regional carbon inventories by Goidts et al. (Goidts et al., 2009) and Schrumpf et al.(Schrumpf et al., 2011). The Taylor series expansion of equation 5.3, which defines the propagated spatial uncertainty of the SOC stocks (ΔSOC_{stock}), is given by Goidts et al. (Goidts et al., 2009):

$$\Delta SOC_{stock} = \frac{\Delta SOC^2}{SOC^2} + \frac{\Delta CF^2}{CF^2} + \frac{\Delta BD^2}{BD^2} + 2\left[\frac{\Delta SOC(1-CF)}{SOC(1-CF)} + \frac{\Delta SOC\cdot BD}{SOC\cdot BD} + \frac{\Delta BD(1-CF)}{BD(1-CF)}\right]$$

(equation 5.6)

with *ΔSOC*, *ΔCF*, *ΔBD* the standard deviations of *SOC*, *CF* and *BD* and with *ΔSOC(1-CF)*, *ΔSOC BD* and *ΔBD(1-CF)* the co-variances within each transect.

5.3.6 Spatial interpolation and prediction of the target variable

Kriging and its variants have been widely recognized as the primary spatial interpolation techniques for land resource inventories starting in the 1970s. Generally, these interpolation techniques solely rely on point observations of the target variable in contrast to regression approaches, which consider the relation of the target variable to spatially exhaustive auxiliary information. In recent years there has been an increasing interest in hybrid interpolation techniques that combine these two conceptually different approaches. Studies applying hybrid interpolation techniques, generally, give better predictions than either single approach (Hengl et al., 2007; Li and Heap, 2011). These interpolation techniques are currently used in a variety of applications, particular in soil carbon sciences (Campbell et al., 2008; Leopold et al., 2006; Lopez-Granados et al., 2005; Yemefack et al., 2005).

Here, we compare the results of different interpolation techniques: simple mean approach (SMA), inverse distance weighting (IDW), ordinary kriging (OK), block kriging (BK) with different block sizes and regression kriging (RK). We transformed all properties prior to the interpolation to account for the normality requirement of the interpolation methods (e.g. SOC stocks were transformed using a power exponent of 0.25: $SOC_{stock,30cm} \rightarrow SOC_{stock,30cm}^{0.25}$).

To calculate the root mean square error (RMSE) of each spatial model, we calibrated the models using the entire dataset except for one sampling point, which serves as a validation point for the predicted and observed soil property. This procedure was than repeated for all sampling points (e.g. leave-one-out cross-validation, following 2008). We thus interpolated each soil property using four different interpolation techniques (IDW, OK, BK and RK) 403 times. IDW was performed using a power exponent of 2, which provided the best fit to the validation dataset. BK was conducted with two different block sizes of 250 m and 500 m. For regression kriging we used factor analysis prior to regression analysis to produce standardized principal components (PCs) as indicator variables (derived from slope, curvature, geology, soil type and land use) to reduce the multicollinearity and to compare the results of fit for different predictors. The regression was performed using a step-wise linear regression of the uncorrelated PCs and the normalized soil properties *(log(SOC),* $CF^{0.5}$*, BD and* $SOC_{stock}^{0.25}$; compare Figure 5.4) (Hengl et al., 2004). According to Gobin et al. (2001) the use of uncorrelated, standardized PCs improves the prediction for soil-landscape modeling. The predictive power of each model is expressed by the regression coefficient between the predicted and observed soil properties using leave-one-out cross-validation.

Furthermore, to assess the interpolation accuracy of the SOC stock based on different sampling sizes and sampling configurations, we randomly divided the dataset into a calibration/interpolation dataset and a validation dataset. The calibration and validation dataset represented 90 % and 10 % of the total dataset, respectively. The splitting was repeated 100 times, to reduce bias resulting from a certain validation/calibration configuration. For model calibration, the calibration dataset was furthermore subsampled to present 10 %, 20 %, 30 %, 40 %, 50 %, 60 %, 70 %, 80 % and 90 % of the total dataset. Based on the split datasets we calculate spatial prediction using the different interpolation techniques (SMA, IDW, OK, BK, RK) for each sub-sample and for each of the 100 model runs. Prediction efficiency was evaluated using the root mean square error (RMSE) of prediction at validation point.

5.4 Results

5.4.1 Spatial variability and controls of SOC stocks

The descriptive statistics of the measured and calculated soil properties up to 30 cm depth for the whole dataset are summarized in Table 5.2. We have chosen 30 cm as a reference depth since the mean soil thickness at the primary cores in the study site is 34 cm. This somehow underestimates the calculated SOC stocks by approximately 10 %, but is comparable to other studies, which apply 30 cm as a reference depth. In general, all soil properties show a high variability. The mean SOC concentration for the entire dataset is 8.49 % with a standard deviation of 7.87 % (the mean SIC is 0.75 % with a standard deviation of 1.77 %). The mean bulk density is 0.86 g cm^{-3} with a standard deviation of 0.28 g cm^{-3}. SOC stock values in the upper 30 cm range between 2.52 and 23.46 kg m^{-2}, with a mean and standard deviation of 8.93 kg m^{-2} and 3.73 kg m^{-2}, respectively. The coarse fractions average 0.30 g g^{-1} with a standard deviation of 0.16 g g^{-1}. The SOC concentration showed with 0.93 the largest coefficient of variation (CV) followed by the coarse fraction with a CV of 0.53. The bulk density and SOC stock had the lowest CVs with 0.33 and 0.42, respectively.

Table 5.2: Minimum, mean, median, maximum, standard deviation (STD) and CV of the measured and calculated soil properties up to 30 cm depth for the entire dataset (n = 403).

	SOC [g g^{-1}]	CF [g g^{-1}]	BD [g cm^{-3}]	$SOC_{stock,30}$ [kg C m^{-2}]
min	0.68	0	0.11	2.53
mean	8.49	0.30	0.86	8.93
median	5.54	0.29	0.85	8.59
max	46.51	0.79	1.9	23.46
std	7.87	0.16	0.28	3.73
CV	0.93	0.53	0.33	0.42

As indicated by the frequency distributions (Figure 5.3) BD-values are normally distributed, SOC are log-normally distributed. CF-values are square root normally distributed and SOC stock are transformed using a power exponent of 0.25. The large variability of SOC stock for different topographic and soil forming factors are confirmed by the scatter- and boxplots in Figure 5.4.

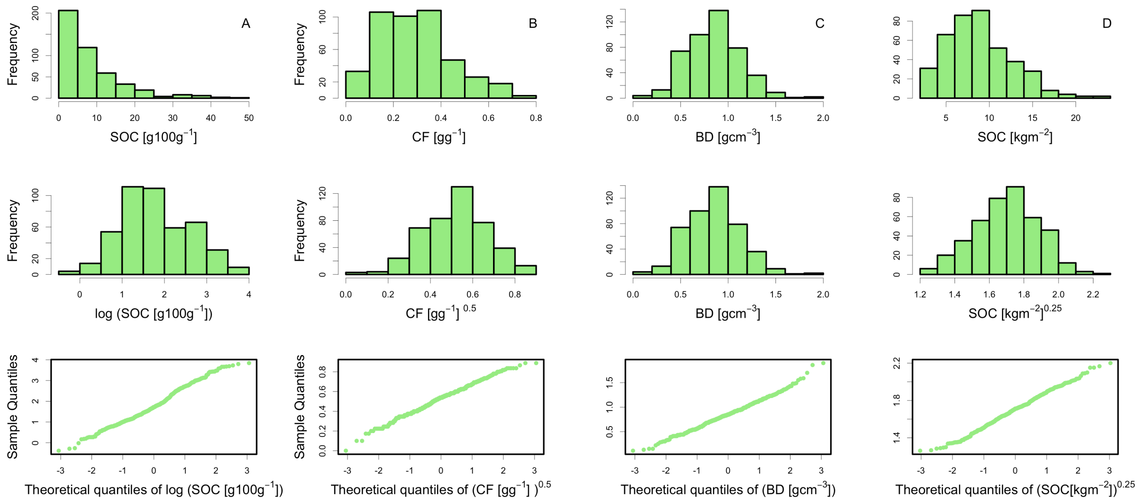


Figure 5.3: Distribution (normal values and sqrt-transformed values) and quantile-quantile plots (qq-plots) of *SOC*, *CF*, *BD* and SOC_{stock}. The variability of SOC stock implies a major control of environmental conditions. The ANOVA suggests that most regional variables (except for plan curvature) show significant differences of the associated SOC stock at a 5 % level but low correlation coefficients (R^2). Lithology and soil type exert the strongest control on SOC stock ($R^2 = 0.20$; $R^2 = 0.15$), while land use, GSI and topographic parameters (elevation, slope, plan curvature, profile curvature) explain only small parts of the observed variability of the SOC stock ($R^2<0.1$). Based on the multiple regression analysis, all site characteristics together explain 44 % of the SOC stock variability (Table 5.3).

Even though there is a strong difference in elevation of 1300 m between the lowest and the highest sampling point, SOC stock does not generally increase with increasing elevation. Concerning lithological variations, highest and lowest SOC stocks are observed in the landslide and Flysch units, respectively. Gleysols, which are characterized by well-developed organic horizons have the highest SOC stocks, in contrast to acidic Cambisols that feature the lowest stocks. The class with grain size index 7 (GSI 7), which represents the highest clay fraction (>30 % clay), indicates the highest SOC stocks in contrast to the GSI 4 (dominated by sandy soils) with lowest values (Table 5.1). As expected, rock and scree are the land cover classes with the lowest SOC stocks, while the open forests have the highest values.

Table 5.3: R^2, F-statistic and p-values of ANOVA concerning the relationship between (SOC [kg m^{-2}])$^{0.25}$ and site characteristics. Light shaded numbers highlight differences at 5 % significant level. Non-shaded numbers represent non-significant differences (=equality).

$SOC_{stock}^{0.25}$	eleva-tion	slope	plan curvature	profile curvature	lithology	soil type	grain size index	land-use	multiple Anova
Multiple R^2	0.070	0.02	0.00	0.025	0.13	0.093	0.00	0.15	0.32
F-statistic	30.35	8.17	0.17	10.44	7.11	5.09	0.23	4.23	4.68
p-value	**0.00**	**0.00**	0.67	**0.00**	**0.00**	**0.00**	0.63	**0.00**	**0.00**

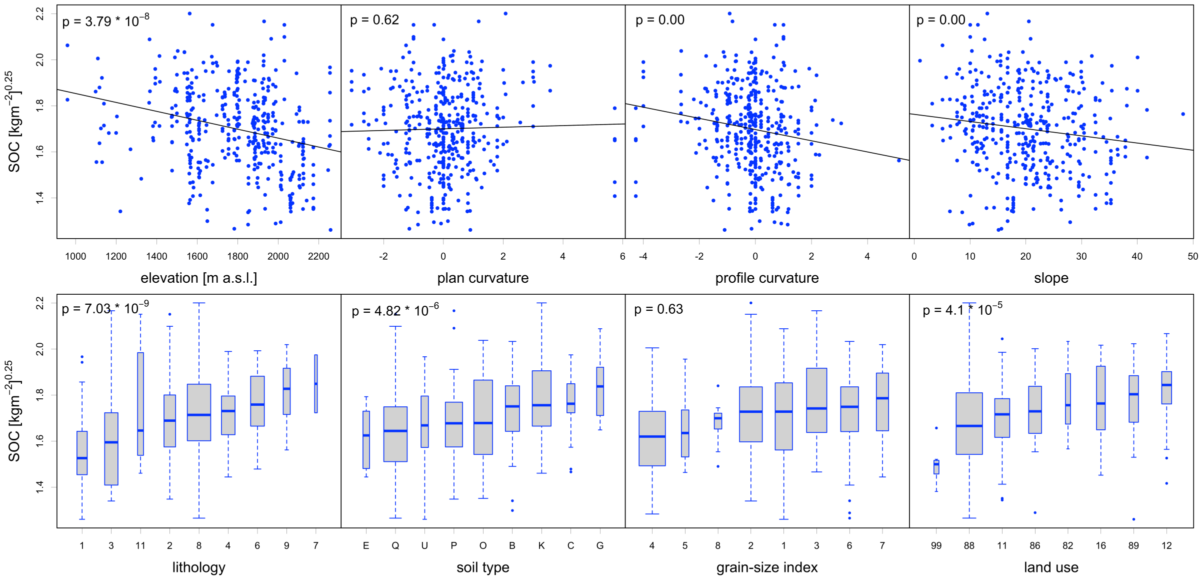


Figure 5.4: SOC stocks as a function of elevation, plan curvature, profile curvature and slope (scatterplot). The boxplots represents the relationship between SOC stock and soil properties as well as soil forming factors (lithology, soil type, grain-size index and land-use). The classes of the soil forming factors in the boxplots are described in Table 5.1. The boxes have widths proportional to the number of sampling points in each box. They represent the minimum, first, second (median) and third quantile and maximum of the SOC-stock. Boxplots and Scatterplots represent all samples up to 30 cm depth below the surface. p-values are derived using the ANOVA test and give significant differences in the case of $p < 0.05$.

5.4.2 Analytical error and effects of spatial uncertainties on SOC inventory

The results of the error calculation are given in form of the coefficient of variation CV, which is calculated as the ratio of assumed and estimated transect-averaged analytical errors (σ) and the standard deviation within each transect to the mean (μ) of each transect given in % (Table 5.4). Differences in the error values obtained by Gaussian error propagation and by Taylor series expansion result from the consideration of the co-variances in the latter.

Table 5.4: Analytical errors and spatial uncertainties of the studied soil properties given as the coefficient of variation (e.g. ratio of the standard deviation/analytical error and the mean value for each transect). Min, max und mean give minimum, maximum and mean values for the 43 transects.

soil property	analytical error [%]			spatial uncertainty [%]		
	min	max	mean	min	max	mean
SOC_c	10	10	10	11.03	123.4	46.79
CF	0.35	14.2	2.8	9.26	133.3	65.0
BD	9.09	11.76	9.97	13.41	88.88	38.27
I	10	10	10	0	0	0
$SOC_{stock\ Gauss}$	17.32	24.63	22.36	22.35	95.69	47.00
$SOC_{stock\ Taylor}$	-	-	-	0.00	444.76	98.50

Regarding analytical errors, the mean standard error of the SOC stock (22.4 %) is largest followed by the bulk density (9.97 %). Concerning spatial variability, the large standard deviation of the coarse fraction provides the highest fraction of the total uncertainty (65.0 %). The spatial uncertainty of the SOC stock, which is calculated based on Gaussian error propagation, varies with a mean of 47 % (Table 5.4). This value is directly comparable to the analytical uncertainty and is almost twice as large as the analytical uncertainty alone with 22.36 %. The mean spatial uncertainty of the SOC stock is 98.50 % based on the Taylor series expansion. Thus considering spatial co-variances between the factors that determine the SOC stock strongly increases the spatial uncertainty. In our case, the co-variance between SOC and BD (R^2=0.65) introduces the strongest contribution to the Taylor error calculation.

5.4.3 Spatial interpolation and regional SOC inventory

The results of the spatial interpolation are presented in Figures 5.5 to 5.7 and in Tables 5.5 and 5.6. Presented maps of interpolated $SOC_{stock,30cm}$ represent the results given for 90 % calibration dataset. In general, all interpolation techniques represent the larger spatial trends with alternating patches of higher and lower SOC stocks (Figure 5.5).

Table 5.5: Summary statistics of interpolated $SOC_{stock,30cm}$ [kg C m^{-2}] using different interpolation methods (as described in the text).

$SOC_{stock,30}$ [kg C m^{-2}]	min	median	mean	Max	SD
mean observed	2.53	8.59	8.93	23.46	3.73
IDW	2.73	8.51	8.62	21.81	1.61
OKR	4.10	8.45	8.58	14.78	1.87
BK1	4.70	8.46	8.56	13.27	1.75
BK2	5.42	8.46	8.52	11.85	1.49
RKR	2.76	8.14	18.54	1986	137.5

However, the applied techniques differ considerably with regard to the reproduced small-scale pattern. The IDW interpolation generates an unrealistic pattern, generally describe as Bull-Eyes, at the location of the sampling points. In contrast, OK and BK resulted in relatively smooth transitions of the SOC stock. Due to the nature of the RK, it represents the most variable distributions, with strong gradients between different soil, geological and land use units. Concerning the modeled minimum, mean and maximum values, IDW, OK and BK are very similar, while RK predicted patches of locally increased SOC stocks. This is reflected also by the high maximum values of SOC stock produced with RK (Table 5.5).

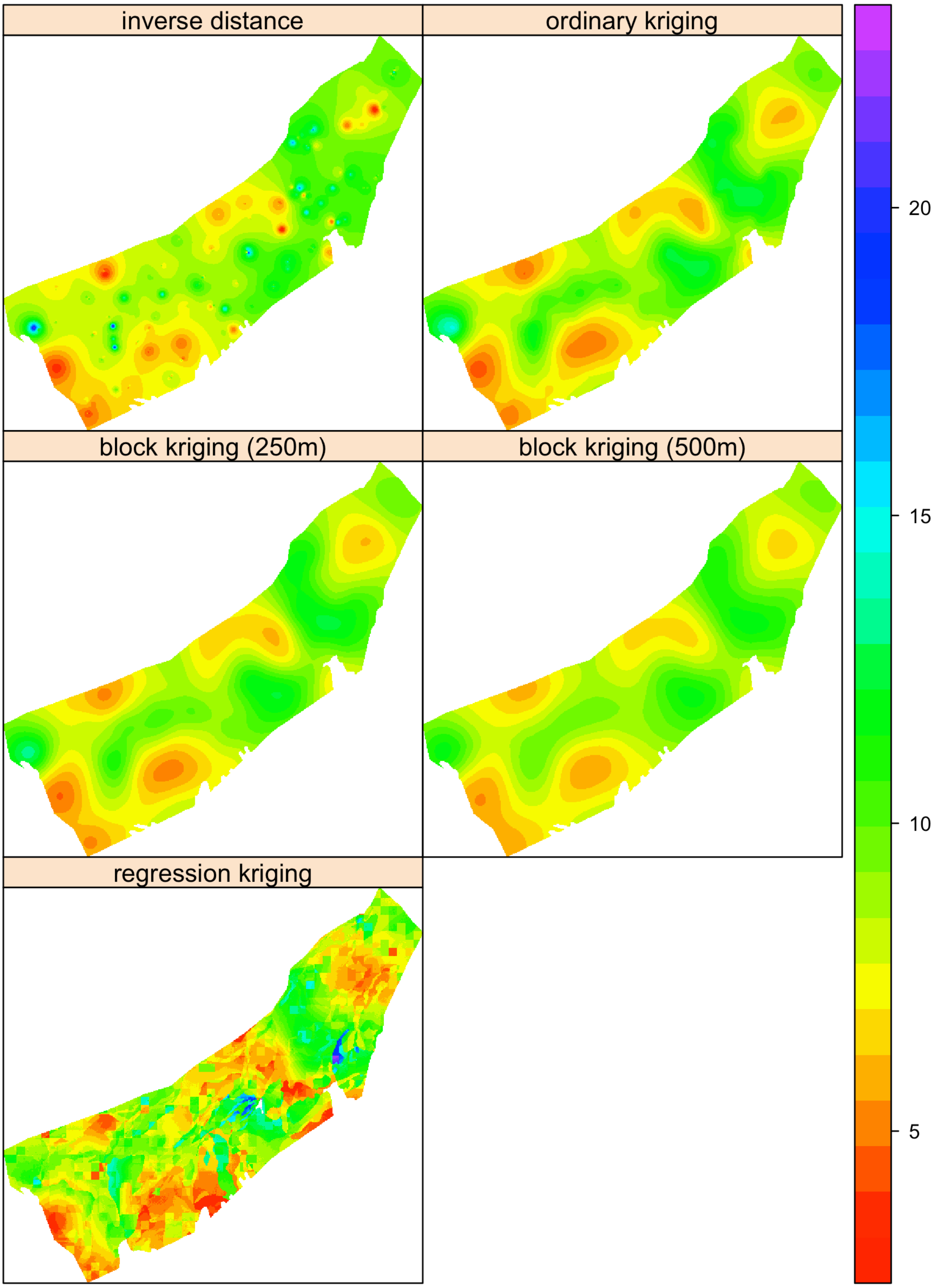


Figure 5.5: Maps of the interpolated results for the entire study site.

Based on linear regression between predicted and observed values OK performs best ($R^2 = 0.38$) whereas IDW and BK for a block size of 500 m show the lowest accuracy (both

$R^2 = 0.32$). RK performs slightly better. The regression coefficient between the predicted and observed value ($R^2 = 0.34$) is similar to the regression coefficient between the measured SOC stocks and the principle components, which is used in the RK (Figure 5.6).

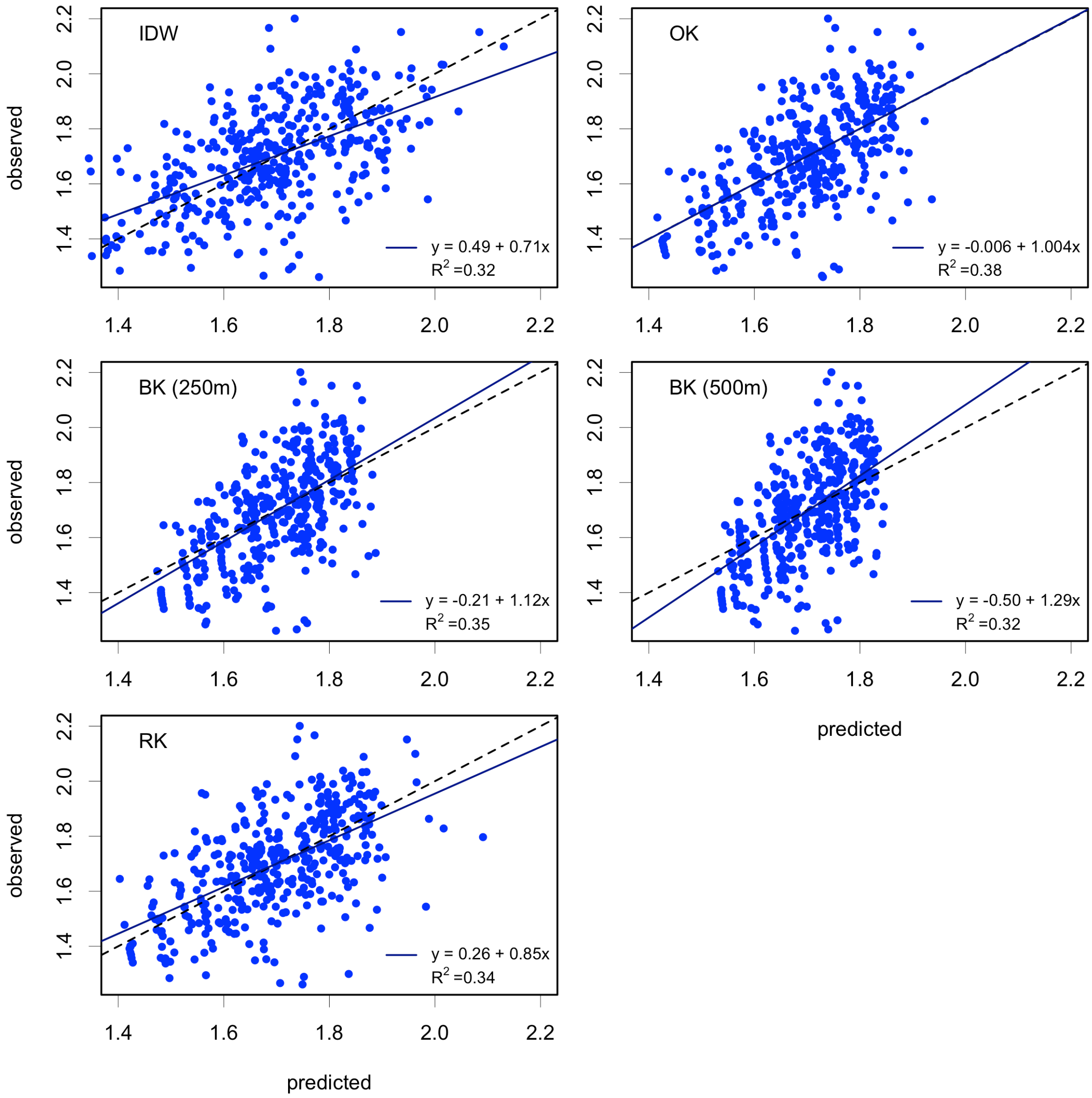


Figure 5.6: Cross validation of interpolated and observed SOC stocks based on inverse distance (IDW:upper left), Ordinary Kriging (OK: upper right), Block Kriging with block size of 250 m (BK: middle left), Block Kriging with block size of 500 m (BK: middle right), Regression Kriging (RK: lower left).

The predictive power of the applied interpolation techniques for SOC, CF and BD is summarized in Table 5.6. While the calculated regression coefficients vary for each soil property, OK shows the strongest and BK (500 m) the lowest predicting power for each property. SOC concentration is the best-predicted property (R^2 ranging between 0.57 and 0.66), while R^2 values for the SOC stock are lowest.

Table 5.6: Comparison of interpolation efficiency for the considered soil properties.

	SOC	BD	CF	SOC stock
stepwise regression with PCs				
• R^2	0.597	0.510	0.364	0.345
Variogram fitting				
• Nugget	0.24	0.037	0.009	0.015
• Sill	0.43	0.039	0.012	0.016
• Range [m]	1540	830	637	761
Prediction efficiency of interpolation (R^2)				
• IDW	0.638	0.488	0.412	0.323
• OK	0.658	0.528	0.442	0.377
• BK (250m)	0.613	0.477	0.391	0.353
• BL (500m)	0.566	0.423	0.317	0.319
• RK	0.637	0.528	0.378	0.338
Spatial uncertainty				
• CV [%]	46.8	38.3	65.0	47.0

Model efficiency in terms of sampling size is given by the RMSE (Figure 5.7): lowest RMSEs (and highest R^2) are associated with OK (for all sampling sizes) followed by RK and BK with a block size of 250 m. While RMSEs for IDW, OK and BK decrease only slightly with increasing sampling size, the RMSE for RK significantly improves for sampling sizes between 40 – 60 % of the sampled data (e.g. between 160 and 240 samples per 8.6 km^2).

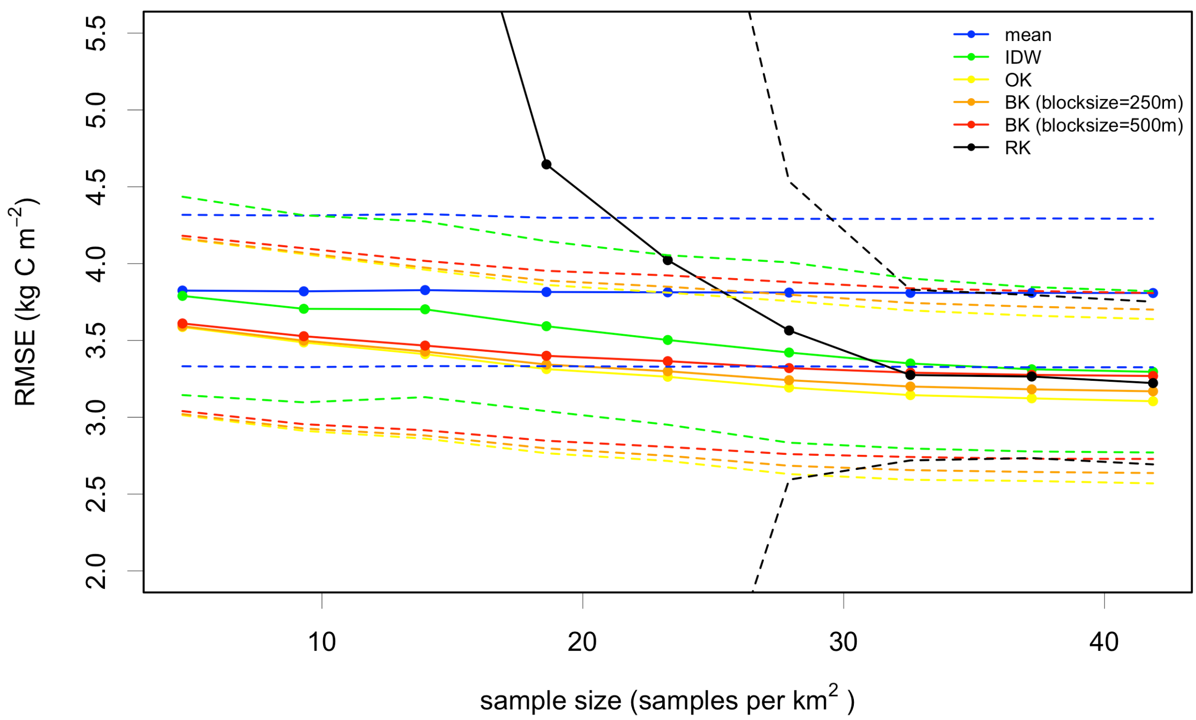


Figure 5.7: Relationship of RMSE and sampling size of different interpolation methods.

5.5 Discussion

5.5.1 Controls of SOC stocks in mountain environments

The presented SOC stocks along an elevation gradient of 1300 m in the Bernese Alps indicate a large spatial variability. Measured SOC stocks in the mineral soil up to 30 cm soil depth ranged from 2.53 to 23.6 kg C m^{-2} (mean: 8.93 ± 3.73 kg C m^{-2}). In contrast to other studies from non-alpine, humid environments (Jobbágy and Jackson, 2000; Meersmans et al., 2008; van Wesemael et al., 2010), no single environmental variable extracted from regional dataset shows a good correlation to the measured SOC stock nor to any considered soil property (Table 5.3). Even though the study area covers an elevation gradient of 1300 m no correlation between SOC stock and elevation was found. While Stutter et al. (2009) and Prichard et al. (2000) revealed a close relation between surface roughness and SOC stocks (e.g. higher stocks on rough surfaces including topographic depressions compared to flat surfaces), our data did not indicate any dependence to profile or plan curvature. In general, missing correlations of topographic parameters to SOC stock suggest a complex interaction and a greater heterogeneity of the environmental factors, which is typical of mountain environments with areas larger than a few square kilometers (Djukic et al., 2010; Körner, 2003). Even considering other environmental factors such as lithology, soil type and land use the explained variability only increases to about 32 % in our study site. These results are more or less in accordance to Homann et al. (1995), who used regression analysis of 499 carbon samples from a forested region in Oregon state (USA) to asses the relation of soil organic carbon to site characteristics. They observed that combinations of site characteristics in a mountainous-forested region explained up to 50 % of the SOC variability.

The large unexplained variability, which is much higher compared to studies in environments with lower topographic relief and intense human impact (Meersmans et al., 2008; Meersmans et al., 2009; van Wesemael et al., 2010), suggests a limited use of regional datasets to predict regional scales SOC stocks in mountain environments. In the case of a low predictability, regional datasets, however, provide an effective mean to spatially distribute the sampling sites, in order to represent for the observed combinations of environmental prediction and to represent the mean SOC stocks of the considered study site.

5.5.2 Interpolation and utility of regional datasets

Average SOC stocks of the whole area (Table 5.5), the general spatial pattern of interpolated stocks (Figure 5.5) and the predictive power (Table 5.6) varied only little between different interpolation models. These results are in contrast to those presented by Kumar and Lal (2011), Phachomphon et al. (2010), and Hengl et al. (2004). Their results suggest that in the case of good correlations between the target parameter and auxiliary spatial information (such as soil maps, land use maps etc.) the use of hybrid techniques (e.g. regression kriging), which utilize the measured spatial information of the target parameter and auxiliary information, have shown to give better predictions than simple interpolations techniques. Independently of the soil property, regression kriging in our study site did not revealed more efficient predictions than IDW, OK or BK. This is true for the for SOC stock, which correlates only weakly with the environmental variables (R^2 = 0.34), but also for the SOC concentration, with a rather high regression coefficient (R^2 = 0.60). As indicated by Hengl et al. (2004) or by Phachomphon et al. (2010), who model the SOC concentrations and stock for Kroatia and Laos, respectively, regression coefficients are not significantly better than in our study (e.g. R^2 = 39 % for the best fit-model in Kroatia, R^2 = 36 % for the best fit-model in Laos). Yet, in both studies, RK provided the highest predictive power. Major differences may arise due to the scale of the study areas and the used regional datasets. The RK modeled a spatial pattern, which is dominantly given by the size of the considered units of the regional datasets (compare Figure 5.5). When high data density together with high spatial variability of the considered dataset meets a regional dataset with relatively low spatial resolution, there might be a general mismatch between the modeled and the observed variability, leading to comparably higher RMSE of the hybrid interpolation technique. This assumption is supported by the strong dependency of RMSE of RK from sample size, which significantly decreases with sampling sizes and thus with the chance that every observed combinations of categorical variables is covered by at least one sampling site. If this is true, a better prediction of the small scale variability of SOC stocks in mountain environments does not only require a high sampling density of soil measurements, but also a high resolution of the applied regional datasets.

Based on a review of spatial interpolation studies, Li and Heap (2011) demonstrated that the efficiency of spatial interpolation methods mainly depend on sampling density, CV and sampling design. Their results indicate that the RMSE of the considered methods generally increased with the coefficient of variation. As shown in Table 5.6, there is no direct link between model efficiency and the CV neither within the study site, nor with the spatial uncertainty given by the CV within the transect. Yet the property with the highest regression coefficient of the stepwise PC-regression (e.g. SOC concentration) shows the best correlation between the predicted and the observed values. Interestingly, this is even true for IDW, OK and BK, which do not rely on auxiliary information as given by the stepwise PC-regression.

In general, we attribute the low variability of the RMSEs with sampling density, to the representative sampling design at the level of the study site.

5.5.3 Sources and effects of uncertainty of soil organic carbon stock calculation

Our results indicate that stratified nested sampling strategy together with the Gaussian error propagation rule provide an effective method to evaluate the sources of uncertainties in the compilation of SOC stocks (Table 5.4). For each considered soil property, the uncertainty associated with its spatial variability within the transects is larger than the uncertainty associated with the analytical precision. This is especially true for the coarse fraction, which introduces the largest error (mean CV = 65 % and maximum CV up to 133.3 %) into the analysis. The CVs given in Table 5.4 are in good agreement to a similar study in the Canadian Rocky Mountains (Hoffmann et al., submitted). There, not only the relative contributions of the soil properties are comparable to our study, but also the absolute CVs are in the same order of magnitude. The large spatial variability of the coarse fraction is also in good agreement with results presented by Schrumpf et al. (2011), suggesting that bulk density and coarse fraction are highly variable in the upper soil layers of cropland and in stone rich soils. Furthermore, Dawson and Smith (2007) suggested that the lack of accuracy in bulk density data is the most severe error term in many SOC estimates. In contrast, Don et al. (2007) observed higher relative variability of SOC concentration compared to the bulk density at two grassland sites in Germany and Goidts et al. (2009) found that organic carbon concentrations and stone contents usually introduced larger errors than bulk density in estimated SOC concentrations in grassland and cropland sites of Belgium. In the Grindelwald area, the coefficients of variability of SOC concentration and bulk density are 46.79 % and 38.27 % and are thus of secondary importance. The differences between Don et al. (2007) and our results might be caused by the relatively high stone content of mountain soils compared to lowland agricultural grasslands.

The CV of SOC stocks based on Gaussian error propagation was 47 % whereas the one based on Taylor series expansion was 98.5 %. Thus, spatial co-variances between soil properties that determine the SOC stock *(*equation 5.1), introduce an additional source of uncertainty (Table 5.4). This is especially true for datasets with a strong co-variance between bulk density and SOC concentration (Catherine and Ouimet, 2008; Lal et al., 2011). The estimated CVs of SOC stocks derived from the Taylor series expansion are directly comparable to results presented by Goidts et al. (2009), who presented values for gently rolling grasslands and croplands in Belgium, which are characterized by strong human impact, humid climatic conditions, and a gentle topography. Their estimates ranged between 5 % and 35 % and are thus much smaller compared to the value we found. Much lower uncertainties, as given by Goidts et al. (2009) indicate that gently rolling grasslands and cropland are much more homogenous. This may be partly caused i) by the missing impact of highly variable and localized geomorphic processes that are responsible for strong gradients of the CF and ii) by strong mixing effects applied by the plough in intensively used croplands.

After all, our results suggest that analytical uncertainties of SOC inventories in mountain environments are of secondary importance. The main source of uncertainty is introduced by the large spatial variability and the strong co-variances of the relevant soil properties. This is especially true for the coarse fraction, which shows the largest spatial coefficient of variation (65 %).

5.6 Conclusion and implications for the compilation of mountain SOC inventories

Our results suggest first a large variability of estimated SOC stocks, and thus a low predictability of these stocks based on regional datasets. Second, no major differences between simple interpolation techniques and more sophisticated techniques that apply the relation to environmental variables were observed. Third, we assume that the representative chosen sampling sites with respect to the regional dataset caused the low sensitivity of the RMSE of the applied interpolation techniques to sampling density. Fourth, the large uncertainty of the stocks that is caused to the large variability of the coarse fraction.

These results have major implications to compile SOC inventories in mountain environments:

- Two-level nested sampling strategies provide useful insights to evaluate the analytical and spatial uncertainty of SOC inventories and to obtain representative regional SOC stocks in mountain environments. The lower level of the nested sampling resembles the resolution of the applied regional datasets. The higher level is given by the larger scale patterns of SOC stocks in the study site. The variability of the soil properties at the lower level compared to the variability within the study site is associated with the predictive power of the regional datasets.
- The spatial uncertainty is analyzed using the site-scale variability given by transects with a length equal to the resolution of the regional datasets. Gaussian error propagation and Taylor series expansion of the measured standard deviations of the measured soil properties provide useful tools to propagate the calculated uncertainty of the SOC stocks.
- To effectively represent the average SOC stock and its larger scale pattern in the study site the sampling sites (e.g. higher level of the nested sampling) should be located to represent the environmental conditions (e.g. area frequency distributions) of the study site. In the case of a high site-scale variability (as suggest for mountain environments) the major benefit of regional datasets is not their power to predict SOC stocks (based on the relationship between soil properties and environmental variables) but to effectively chose sampling sites to represent the environmental conditions of the study site.
- In the case of low correlations between soil properties, SOC stocks and regional datasets, there are no consistent findings about which factors affect the performance of the spatial interpolators. In the case of representative located sampling sites at higher level of nested sampling, a low sensitivity of the RMSE with respect to sampling density is expected.
- An effective sampling design for alpine SOC stocks should represent the large variability of the coarse fraction. Since the variability of the coarse fraction is mainly controlled by the small-scale variation of the parent material through effective sediment transport and accumulation processes, we state that detailed geomorphological mapping provide the most promising regional predictor of alpine SOC stocks.

6. Synthesis

This thesis intends to improve our understanding of the linkages between environmental variability and the uncertainty of SOC stock assessments in dynamic geomorphic systems. The presented case studies provided new information on the controlling properties of SOC inventories in arid and mountain environments that are characterized by a high spatial heterogeneity and a high sensitivity regarding environmental changes. A major focus of this PhD was driven towards the analysis of the site-scale variability of soil properties and the sources of uncertainties associated with the compilation of SOC inventories in complex and changing ecosystems. In general, the results indicate that nested sampling designs in combination with the Gaussian error propagation provide an effective tool to identify sources of uncertainties and to improve the methodology of future high-resolution SOC inventories in arid and alpine environments.

The results of the single case studies were already discussed above in more detail. However, the following synthesis briefly summaries the results of the case studies (chapter 6.1 and 6.2) and then compares the results and discusses the major findings (chapter 6.3) regarding the questions raised in the introduction (chapter 1). The characteristics of the study site and the results of the three case studies are summarized in Table 6.1.

6.1 SOC stocks in arid and mountain environments

The first case study aimed to identify the relationship between surface characteristics, vegetation coverage, SOC concentration and -stocks in the arid northern Negev in Israel. The results show a large spatial variability of SOC, soil bulk density and soil thickness (Table 6.1). They indicate that soils cover 30 % of the study area and are on average 18 cm deep. The estimated SOC stock in this area ranges between 0 and 3.03 kg C m^{-2} with a mean of 0.58 kg C m^{-2} (median: 0.31 kg C m^{-2}) and a standard deviation of 0.61 kg C m^{-2}. The differences in SOC stocks between ecohydrologic units on the north- and south-facing slopes imply a high relevance of eco-climate and thus a high sensitivity to potential climate changes. The results confirm that conceptual approaches, which explain the spatial patterns of vegetation cover on rocky desert slopes in the Negev, can also be applied to SOC stocks. In addition to climate-driven differences between aspect and slope position, the ecohydrologic units take into account changes of small-scales surface properties. The small-scale variability is mainly caused by lithology-driven differences of the microtopography, which provides accommodation space for fine sediment accumulation and soil formation in fissures and on bedrock steps. Thus, significant differences of SOC stocks as well as vegetation densities between ecohydrologic units demonstrate that small-scale surface properties provide a further control on the presence or absence of soils and thus on the amount of SOC storage. The results strongly suggest that the microscale water supply and NPP are the limiting condition for the formation of SOC in arid, rocky deserts. Even this amount is smaller than in more humid environments, it is of major importance for the functioning and thus conservation of arid ecosystem.

The two field studies in mountain ecosystems aimed to estimate the site-scale variability of soil properties and error sources to calculate SOC stocks. First the site-scale variability of relevant soil properties (bulk density, coarse fraction and SOC concentration) and SOC stocks was estimated. Second, the relation of SOC stocks to environmental characteristics that influence soil formation and SOC storage (elevation, slope, aspect, soil texture, stand age, lithology, geomorphic environment) was analyzed. Third, the unexplained variability caused by the limited resolution of the available data was calculated using a stratified nested sampling approach. We therefore analyze the propagation of analytical measurement errors and spatial differences based on Gaussian error propagation and Taylor series expansion. Finally, the main sources of these uncertainties were identified using different interpolation methods and simple mean predictions. The identification of uncertainties provided a methodological framework for spatial prediction and give implications for improving future SOC stocks in mountain environments.

The estimated SOC stocks in both mountain sites were very similar (Table 6.1) with a mean of 6.40 [kg C m^{-2}] in Kananaskis (SD = ± 5.58) and Grindelwald with a mean of 8.93 [kg C m^{-2}] (SD = ± 3.73). Both studied mountain sites shows a comparable large spatial variability of the soil properties with largest variability for the coarse fraction and the SOC concentration. Comparable results are shown by the coefficient of variations for the coarse fraction and the SOC concentration in Grindelwald and Kananaskis (e.g. 65 % and 63.8 % for the CF and 46.8 % and 40.1 % for SOC). Nevertheless major differences between the uncertainties of the bulk density (e.g. 38 % in Grindelwald and 23.5 % in Kananaskis) were the main reason of the higher uncertainty of the SOC stock in Grindelwald (47 %) than in Kananaskis (38 %). A higher level of uncertainty was introduced in the Grindelwald area through the covariance between the SOC concentration and the bulk density (R^2=0.65). Furthermore the mountain studies presented large variability by low predicting power of the site characteristics (extracted from available data such as DEM, geological and terrain inventory map) and SOC stocks.

Table 6.1: Summary and main conclusions of the three case studies.

	Israel	Kananaskis	Grindelwald
No. of sites /samples	82	221 (17 transects with 13 sampling points)	408 (43 transects with 8 sampling sites)
sampling method	• N-S cross-section through the studied valley	• mix of stratified random and systematic sampling • 17 transects (length = 36 m) with one primary core and 12 secondary cores	• stratified nested sampling • 43 transects (length 30 m) with one primary core and 8 secondary cores
Study area			
size [km^2]	0.045		8.6
MAT [C°]	20	1.03	5.9
MAP [mm]	91	442-960	1200- >3000
elevation [masl]	485-535	1585-3220	700-2500
geology	• limestone formations	• Paleozoic carbonates • Mesozoic clastics (shales, mud-, and sanstone)	crystalline Aarmassive including limestone, flysch and molasse
soil	• desert brown lithosols • aeolian loess-like sediments	Brunisols; Regosols, Gleysols	Cambisols; Regosols; Rendzina
regional datasets	• aerial photograph • mapped vegetation coverage • soil cover • soil depth	• digital elevation model (30 m) • terrain inventory map, forest stand age • geological map • forest stand-origin map • MAAT calculated based on DEM	• digital elevation model (10 m) • areal statistic of CH (100*100 m grid) • soil map (1:25.000) • geological map (1:25.000) • ground truth: mapped land-use
Measured soil properties (mean ± SD (CV))			
SOC [g 100g^{-1}]	0.86 ± 0.68 (78.9 %)	4.5 ± 3.5 (77.7 %)	8.49 ± 7.87 (92.6 %)
CF [g 100g^{-1}]	12.0 ± 9.74 (81.0 %)	0.36 ± 0.38 (105.5 %)	0.30 ± 0.16 (53.3 %)
BD [g cm^{-3}]	1.30 ± 0.27 (20.7 %)	0.89 ± 0.23 (25.8 %)	0.86 ± 0.28 (32.5 %)
soil depth [cm]	18.7 ± 11.1 (59.5 %)		
SOC stock [kg C m^{-2}]	0.58 ± 0.61 (105.2 %)	6.40 ± 5.58 (87.1 %)	8.93 ± 3.73 (41.8 %)

Spatial uncertainty within transect variability (CV)			
SOC_c [g 100g^{-1}]		40.1	46.79
CF [g 100g^{-1}]		63.8	65.0
BD [g cm^{-3}]		23.5	38.27
SOC $stock_{Taylor}$ [kg C m^{-2}]		38.0	47.0
SOC $stock_{Gauss}$ [kg C m^{-2}]		40.8	98.50
GENERAL OUTCOME			
dominating environmental predictors	• vegetation cover, aspect	• lithology, geomorphic environment, slope, aspect	• clay content, land use, lithology
main results	• high correlation to vegetation coverage • aspect driven climate differences → modification of lithology driven surface propert§ies	• lithology and geomorphology dominates SOC stock → largest variability due to CF • effective sampling strategy should focus on the spatial distribution of the coarse fraction, while the analytical precision of these measurements is of secondary importance • large variability is presented by low predicting power of the site characteristics and SOC stocks • suggest a complex interaction of SOC stocks and environmental conditions in mountain environments	• very low correlations to environmental conditions but high co-variances between soil-properties • soil properties need a large number of spatially distributed measurements, while soil properties characterized by large analytical errors require high quality but low quantity measurements • data density needs to be adapted to the scales of the relevant objective of the study
outlook and implications for improving future SOC stocks	• up-scaling based on remote sensing of vegetation coverage	• consideration of the whole set of available data when establishing SOC inventories • histogram analysis of CF to represent geomorphic environments • better representation of the complex interaction of small-scale variables involved in SOC stock variability and soil-forming properties and processes • larger number of measurements and a better representation of geomorphic processes that introduces a high degree of spatial variability of SOC-relevant soil properties	• sampling density dependent on main research question • average values require low data density, analysis of small scale pattern requires high data density • future SOC inventories should focus on the quality of sampling (e.g. sampling design) and auxiliary environmental predictors

6.2 Discussion of the guiding research questions

Based on the results from the three case studies I attempt to answer the major research questions that were raised in the introduction (chapter 1):

Question 1: Which soil property introduces the largest variability and thus the largest uncertainty in the calculation of SOC stocks?

All three studies are characterized by strong gradients of the environmental conditions. In the arid study area Sede Boker, the variable surface properties lead to the largest complexity. Surface properties range between soil free bedrock surfaces, which prohibit the formation and storage of SOC, to sediment filled bedrock fractures and completely soil covered colluvial deposits. These surface characteristics strongly control the surface runoff, the storage potential for fine sediments and the availability of soil moisture. While aspect-driven differences of the solar radiation influences the heat budget and thus the evaporation, hot spots of vegetation coverage and SOC formation are associated with the existence of fine sediment and increased soil moisture.

In contrast to the arid study site with minor topographic relief, strong topographic gradients in the mountain study areas introduce the highest variability. Steep slope gradients control the available heat budget, the soil water availability and geomorphology in these areas. Furthermore, steep slope gradients provide a high potential energy for geomorphic processes, which have a strong impact on the stability and texture of the parent material. Due to the small-scale variability of the topographic driven conditions for the transport and accumulation of sediment in mountain areas, geomorphic processes generally generate a very high spatial variability of the properties of the parent material. For instance, stable surface conditions with plenty of fine material and high soil moisture contents can be found in a very short distance to coarse-grained, well-drained and unstable debris accumulations.

The strong gradients of the environmental conditions in all study sites result in a large small-scale variability of the soil properties that determine the SOC stocks according to equation 2.1:

$$SOC_{stock} = SOC \times BD \times (1\text{-}CF) \times l$$

In all three case studies the coefficients of variation (CV) associated with the spatial variability of BD, CF, SOC and l are much larger than the errors associated with the analytical techniques to estimate these soil properties. The three different environments confirm that the highest variability of all SOC controlling factors is displayed by the coarse fraction. SOC concentration shows the second largest variability of the independent variables and the bulk density shows the lowest variability of the independent variables. The large spatial variability associated with these soil properties is propagated through the calculation of the carbon stock at the sampling points. Consequently, the estimated SOC stocks show a large uncertainty.

The variability of the soil properties and the SOC stocks at Sede Boker is associated with differences in slope-aspect and NPP of the ecohydrologic units along the rocky desert slopes. In accordance to earlier studies taken in this environment, these results imply a dependency of SOC stocks on the relative moisture supply, which is given by surface runoff and aspect driven differences of evaporation. Thus the strong variability is introduced through the non-continuous soil coverage and the local soil/sediment deposition in small depressions and bedrock fissures.

In contrast to Sede Boker, the studied mountain sites were completely covered with sediments with a large variability of the coarse fraction and SOC concentration. The CVs for the coarse fraction and the SOC concentration in Grindelwald and Kananaskis were very similar (e.g. 65 % and 63.8 % for the CF and 46.8 % and 40.1 % for SOC). Major differences between the uncertainties of the bulk density (e.g. 38% in Grindelwald and 23.5 % in Kananaskis) were the main reason of the higher uncertainty of the SOC stock in Grindelwald (47 %) than in Kananaskis (38 %). A higher level of uncertainty was introduced in the Grindelwald area through the covariance between the SOC concentration and the bulk density (R^2=0.65), which explained the main differences of the uncertainty calculated by the Taylor series expansion. In the cases of strong covariances a high number of samplings is required for the relevant soil properties.

To conclude, arid and mountain environments are settings with high spatial gradients of the environmental conditions that translate to a high spatial variability of the soil properties that determine the SOC stocks. Even though the reasons for this variability are fundamentally different in arid and mountain environments, the coarse fraction presented the largest variability and introduced the largest uncertainty of the calculated SOC stocks in all three study sites. Due to the close link between the coarse fraction of the parent material and the geomorphic activity, I state that detailed geomorphic maps, which represent the dominant geomorphic processes and their deposits, represent an indispensable tool to improve regional SOC stocks in arid and mountain environments.

Question 2: How do regional environmental data present the spatial variability of the SOC stocks and how do these datasets contribute to the compilation of regional SOC stocks?

In all three case studies, regional datasets (such as digital elevation models and geological, soil and land use maps) that are assumed to represent some of the soil forming factors were used to test the link between the regional datasets and the measured SOC stocks. The regional datasets provided a low predictive power of the measured SOC stocks in the arid and mountain environments. For instance, the stepwise regression, which applied the available regional datasets, explained only ~34 % of the variability in the Grindelwald area. Due to equivalent results presented by the boxplots of SOC stocks stratified according to different environmental conditions, a similar low explainability of the regional datasets in Sede Boquer and the Kananaskis area can be assumed.

The low predictive power of the regional dataset mainly follows from the discrepancy of the site-scale variability of the soil forming processes and the comparative low resolution of the regional datasets. The mismatch is expressed by the variability of the measured soil properties along the studied transects (compare chapters 4 and 5), which lengths were chosen to represent the spatial resolution of the regional dataset (compare research question 1).

Assuming that the regional dataset present the dominant soil forming factors, these considerations suggest that regional datasets with a higher spatial resolution are needed to gain a higher spatial predictability of SOC stocks in arid and mountain environments. However, the regional datasets represent simplified models of the environmental conditions that were generally not optimized for the calculation of SOC inventories. For instance, the geological and soil maps provide insufficient information of the grain size (an thus the coarse fraction); and land use maps do not differentiate between the forest types and ages. If this is true regional datasets with a higher spatial resolution do not necessarily provide a better prediction. In fact, regional datasets, which are optimized for the calculation of SOC stocks may substantially improve spatial predictions. The results from the Negev desert indicate a good example on the applicability of an optimized dataset, which relied on a process-based understanding of the spatial patterns of the dryland ecogeomorphology and stratified the study site into ecohydrologic units of similar surface process regimes. The significant differences of SOC stocks as well as vegetation densities between ecohydrologic units demonstrate that small-scale surface properties provide the dominant control on the presence or absence of soils and thus on the amount of SOC storage. Thus, the result confirms that the spatial distribution of the ecohydrologic units, which consider the small-scale variability of the surface properties, explained the spatial patterns of vegetation cover and the SOC stocks, which are strongly correlated in the Negev rocky desert.

A detailed mapping or modeling procedure that considers the spatial variability of the sediment texture (as suggested in the Kananaskis case study) provides a high potential to decrease the uncertainty of mountain SOC inventories, while the analytical precision of these measurements is apparently of secondary importance.

Even though available regional datasets, so far, have a low predictive power, their main advantage is the identification of the sampling locations before field sampling.

The low variability of the RMSE in the Grindelwald studies was attributed to the fact that the sampling locations represent the environmental conditions of the study site. The representativeness was achieved by the areal frequency distribution analysis of the combinations of environmental conditions before field sampling. In the case of a representative sample set, all randomly selected subsamples are assumed to be representative and therefore predict the average mean SOC stocks within the study site.

To summarize, regional datasets explain only small parts of the observed variability of the soil properties. In fact, the relationship between environmental conditions and the soil forming processes seems to be distorted by the complex interaction between the environmental variables and the large spatial heterogeneity in arid and mountain areas. While the predictive power of the regional datasets remain limited, they provide helpful information to select the sampling locations used to compile the desired SOC inventory. However, more SOC inventories that cover the full range of the observed complexity (and not simplified sampling designs that consider the variation of only one parameter) in arid and alpine environments is required.

Question 3: What are the major implications to improve regional SOC inventories?

Overall the results of the three different field studies imply that future SOC inventories in heterogeneous environments should focus on the quality of sampling (e.g. sampling design) and auxiliary environmental predictors. Better procedures are needed for optimizing sampling with regard to cover the spatial variation of the environmental conditions at various spatial scales. As indicated by the results of the three study sites, larger scale (e.g. regional) patterns of SOC stocks are driven by different processes than those, which introduce the small-scale (e.g. site scale) variability.

To cope with the different scales of variability, a two-level nested sampling design was applied in the mountain case studies. The nested sampling strategy, which was designed to represent the spatial resolution of the available data on the one hand and to estimate the sub-pixel variability of soil properties and SOC stocks on the other hand, in conjunction to the Gaussian error propagation and the Taylor series expansion was helpful to discriminate sources of uncertainties and to identify the relevant scales of spatial variability.

While mainly two nested levels (e.g. the transect and the studied area) were applied in the PhD thesis, the nested sampling concept provides the potential to include even more levels and to identify more relevant scales to improve the assessment of SOC stocks.

7. Guidelines to compile SOC inventories in dynamic geomorphic systems

Based on the results of the three present case studies (for a summary see chapter 6.1) and the identified limitations of regional SOC inventories (compare discussion of the guiding research questions in chapter 6.2), the following guidelines for the compilation of SOC inventories in dynamic geomorphic systems were developed. The guidelines are based on a stratified, two-level sampling design. The upper level represents the regional patterns of the SOC inventory, while the lower level defines the unexplained site scale variability.

1. **Acquisition of regional dataset**
   a) **Stratifying regional datasets and identify sampling locations**

      The results from the Grindelwald area, indicates that the number of sampling sites should be chosen to represent the variability of the environmental conditions given by the regional datasets. Therefore, each combination of environmental conditions should be covered by at least one sampling point (or sampling transect), as applied by the stratified sampling scheme in the Grindelwald case study. This is especially necessary for the regression kriging in which the environmental conditions are linked to the considered soil properties. The stratification represents the regional SOC patterns of the nested (two level) sampling design, in contrast to the scale of the site variability.

      As indicated by the large uncertainty introduced by the CF, a detailed geomorphic map, which considers the grain size and texture of the accumulated sediments, is essential to improve spatially interpolated SOC stocks. Therefore, aerial orthophotos in conjunction with high-resolution digital elevation models could be used to identify and map the dominant geomorphic process domains (e.g. rockfall deposits such as talus slopes, debris flow deposits, moraines, landslides). Subsequently, fieldwork is required to check the geomorphic maps, which were derived from the orthophotos, and to establish coarse fractions of the deposits associated with different geomorphic processes (e.g. downstream fining as observed in Kananaskis).

   b) **Define the scale of the site variability**

      The scale of the site variability is defined by the resolution of the available datasets. As indicated by the mountain case studies, the length of the studied transect should be chosen to be similar to the mean spatial resolution of the considered regional datasets. In this case, the variability within the transects represents the unexplained variability of the soil properties, which allows to evaluate the sources of uncertainty of the relevant soil properties (e.g. SOC, BD, CF and soil depth). However, in geomorphic active environments, the scale of variability of the soil properties might be much smaller that the resolution of regional datasets. In this case, the ability to obtain or compile (e.g. through remote sensing and DEM analysis) regional dataset with a higher spatial resolution needs to be tested.

2. Field sampling

The aim of the field sampling is to establish the variability of SOC stocks within the study site and the unexplained variability given by the limited spatial resolution of the regional datasets (see acquisition of regional datasets). In addition to the horizontal variability, the vertical changes of the soil properties needs to be addressed. Ideally, the entire soil columns should be sampled. In facts, this is very time consuming task, especially in coarse grains soils as given in arid and mountain environments. In conjunction to the two level soil sampling approach, we therefore suggest to divide the sampling into primary and secondary cores. Primary cores define the center of each studied transect, while secondary cores are the remaining cores of the transect:

a) Sampling of the primary core

Sampling at the primary core should (if possible) cover the entire soil column to facilitate a detailed description of the soil type and to evaluate changes of the soil properties with depth. This furthermore allows the calculation of mean soil thicknesses and to estimate the depth depended fractions of SOC stocks.

b) Sampling of secondary cores

To facilitate a cost-effective sampling design, sampling at secondary cores is limited to the upper 10-20 cm. Sampling of the secondary core is conducted in order to estimate the relevant soil properties SOC, BD and CF.

c) Sampling of additional soil properties

The results from the mountain case studies indicated that the CF introduces the highest spatial uncertainty in the calculation of SOC stocks. Thus, additional CF-samples along the transect are helpful to increase the representativeness of the measured CF values and to better constrain the uncertainties of the calculated SOC stocks.

3. Laboratory analysis

As suggested by the results from Kananaskis and Grindelwald, the analytical uncertainties associated with the laboratory techniques to estimate the SOC, BD and CF are an order of magnitude smaller than the spatial variability observed in the field.

However, to constrain analytical uncertainties, replicate measures of the same sample or measuring samples taken from the same location and same soil horizon are necessary.

4. Modeling of SOC stocks

a) Calculation of spatially distributed SOC stocks

The results from the Grindelwald case study showed that reliable mean SOC stocks calculated for larger areas are given even by a small number of sampling points. This, however, requires that the spatial distribution of the sampling points within the considered region is representative of the environmental conditions in the same area.

Interpolation techniques (such as inverse distance, ordinary kriging, block kriging, and regression kriging) were used in this study to obtain spatially distributed SOC inventories. In the presented PhD, the application of the interpolation was limited to the Grindelwald area, since the sampling in the other both case studies was not sufficient to represent the environmental conditions. Based on the results from the Grindelwald area, none of the applied interpolation algorithm was significantly better than the others and more detailed analysis of the advantages and disadvantages are required.

b) Evaluation of uncertainties

Using a two-level sampling design as defined above, the Gaussian error propagation and the Taylor series expansion provide effective tools to evaluate the spatial uncertainties of the calculated SOC stocks. While the Gaussian error propagation was used to compare uncertainties associated with analytical errors and spatial uncertainty, the Taylor series expansion provided more convenient results in the case of strong co-variances between the relevant soil properties, as shown by the results from the Grindelwald case study.

Furthermore, the “one leave out cross validation” as applied in the Grindelwald case study provided an effective tool to calculate uncertainties associated with the applied interpolation techniques. However, more case studies are needed to evaluate the advantages and disadvantages and the relation of the one leave out cross validation with the applied error calculations using the Gaussian and Taylor error propagation.

8. Outlook

The results of this PhD provided new information on the controlling factors of SOC inventories in arid and mountain environments that are characterized by a high spatial heterogeneity and a high sensitivity regarding environmental changes. The literature review on SOC inventories in those dynamic geomorphic systems indicated that the number of comparable studies is very limited and demonstrates that the studies are characterized by different measurement techniques, variable reference soil depth and different interpolation techniques. Generally the differences in SOC stocks between published studies may thus not represent environmental conditions but simply different applied methodologies. Hereafter more case studies using a comparable methodology are necessary to evaluate the importance and potential changes of SOC in arid and mountain environments.

The PhD indicated the high potential of the stratified nested sampling design, which is adapted to the soil forming processes and the spatial resolution of the available regional dataset. Stratified nested sampling designs do not only provide reliable estimates of SOC stocks, but also help to improve our understanding of the spatial uncertainties of SOC stocks. However, more comparable and detailed SOC stocks are needed to verify the results of this study. Additional research in arid environments should test the link between vegetation coverage and SOC stock in order to apply these to larger areas based on regional vegetation distributions using remote sensing techniques. In mountain environments, special focus should be given on the link between SOC stocks and the spatial variability of the coarse fraction. Detailed geomorphic mapping, with a special focus on the spatial variability of the coarse fraction, could provide high-quality auxiliary environmental predictors. Thus more detailed SOC inventories focusing on the effects of geomorphic processes are needed.

In changing alpine and mountain environments, which are strongly affected by changing geomorphic processes (e.g. increased geomorphic activity, due to lower vegetation coverage under more arid conditions or due to permafrost-associated destabilizing of sediment and rock walls), geomorphology-focused SOC inventories may help to better constrain future changes and to better identify the relevance of arid and mountain soils in the global carbon cycle. Thus, future research might elucidate potential climate and site-specific differences in SOC stocks and should help to derive common SOC stock concepts, which can be central to the field of biogeomorphology. In a world with increasing anthropogenic disturbances (e.g. increase CO_2 emission) climate change and ecological restoration, to name only a few, a conceptual framework of SOC stock assessments can be suitable to address these concerns and help to predict changes, relevant for future generations.

Appendix A: Table A1

Summary of literature review regarding the feedback between environmental factors and soil properties (for description see text in Chapter 2)

reference	feedback	sign of FB
elevation and temperature		
Brady and Weil (2002)	SOM production and destruction strongly influenced by MAT	+
Bolstad and Vose (2001)	SOC stocks significantly higher at high elevations (>1150m) than at low elevations (>900m)	+
Leifeld et al. (2005)	higher SOC % at high altitudes explained with a limited C turnover	+
Perruchoud et al. (1999)	no strong relationship between SOC stocks and climatic signatures	0
Tan et al. 2004 (2004)	percentage of the variability of SOC pools that can be explained through elevation can be ignored	0
Djukic et al. (2010)	no consistency in the change of SOC stock with elevation	–
Garcia-Pausas et al. (2007)	altitudinal changes have to be looked at in combination with slope and aspect because C-content in high altitudes depends on the microclimatic conditions which in turn are related to topographic position	0
Sheikh et al. (2009)	stocks of SOC were found to be decreasing with altitude	–
Schawe et al. (2007)	did not detect any trend in SOC stocks with elevation. The reason might be that the large variation in SOC stocks among different micro-sites was larger than any trend in SOC stocks with altitude.	–
aspect and slope position		
Perruchoud et al. (2000)	SOC is related to the slope gradient and aspect	+
Homann et al. (1995)		+
Lal (2005a)		+
Egli et al. (2009)		+
Garcia-Pausas et al. (2007)	Topography influences SOC stocks by affecting soil freezing and thawing, snow melting and the constitution of the plant communities to only mention a few	+
Tan et al. (2004)	slope only had a slight impact on SOC variation suggesting that the influence of slope is predominated by other factors	0
bedrock material and texture		
Lal (2005b)	coarser soils have lower SOC % than silt loam or sandy loam soils	+
Banfield et al. (2002)	clay content can be used as a predictor/modifier of biomass accumulation on upland sites	+
Tan et al. (2004)	• heavy texture favored SOC sequestration in all land uses. • significance of individual site variables was generally in the order of soil taxon>drainage>texture>slope>elevation.	+
Brady and Weil (2002)	• with rising clay fraction, the organic carbon content is said to rise.	+
Leifeld et al. (2005)	• within the texture classes the clay content plays an important role for SOC % within the first 20cm of the soil.	+
Hoffmann et al. (2009)	• weak or absent correlation between clay and TOC.	–
pH		
Heckmann et al. (2009)	• no direct correlation between pH and SOC content.	0
Falloon and Smith (2009)	• carbon turnover is faster in basic soils compared to acidic soils	+
Djukic et al. (2010)	• soil pH is thus dependent on the presence or absence of conifers.	+

topography & geomorphic processes		
Berhe et al. (2008)	• SOC content change depending on the terrain unit.	+
Liechty et al. (1997)	• no long-term change in the carbon storage was found due to changes in the microtopography.	–
Yoo et al. (2006)	• strong curvature-dependent SOC storage caused by curvature-dependent soil erosion/production and their integrated effect on soil thickness.	+
Prichard et al. (2000)	• flat surfaces store less SOC than mounded surfaces.	+
Burke (1999)	• spatial variability in SOM is most strongly related to topography.	+
Hancock et al. (2010)	• SOC is related to catchment geomorphology and hydrology.	+
vegetation and stand age of the forest		
Homann et al. (1995)	• the age of the forest is believed to affect SOC stocks.	+
Luyssaert et al. (2008)	• topsoils in old-growth forests have been shown to accumulate atmospheric carbon at a high rate.	+
Zhou et al. (2006)		
Pregitzer et al. (2004)	• topsoils in old-growth forests have increasing soil C pools with time.	+
disturbance due to human activity		
Morgan et al. (2010)	• agricultural lands: best management practices for improving soil C storage.	+
Czimczik et al. (2005)	• effects of reforestation, deforestation, and afforestation on carbon storage in soils.	+
Bell and Worall (2009)	• differences in land management practices could be responsible for more than 30 % variation than either soil series and land use.	+

Bibliography

This bibliography does not contain references that are limited to chapter 3. For references on chapter 3 see page 28-30.

Allen, D.E., Pringle, M.J., Page, K.L., Dalal, R.C., 2010. A review of sampling designs for the measurement of soil organic carbon in Australian grazing lands. The Rangeland Journal 32, 227-246.

Amundson, R., 2001. The Carbon Budget in Soils. Annual Review of Earth and Planetary Science 29, 535–562.

Arrouays, D., Pelissier, P., 1994. Modeling carbon storage profiles in temperate Forest hunic loamy soils of france Soil Science 157(3), 185-192.

Aufdenkampe, A.K., Mayorga, E., Raymond, P.A., Melack, J.M., Doney, S.C., Alin, S.R., 2011. Riverine coupling of biogeochemical cycles between land, oceans, and atmosphere Frontiers in Ecology and the Environment 9(1), 53-60.

Banfield, G.E., Bhatti, J.S., Jiang, H., Apps, M.J., 2002. Variability in regional scale estimates of carbon stocks in boreal forest ecosystems: results from west-central Alberta. Forest Ecology Management., 169, 15-27.

Batjes, N.H., 1996. Total carbon and nitrogen in the soils of the world. European Journal of Soil Science, 47, 15 11- 163.

Bell, M.J., F. Worrall, 2009. Estimating a region's soil organic carbon baseline: The undervalued role of land-management. Geoderma, 152, 74-84.

Berhe, A.A., 2006. Storage, Replacement, Stabilization, and Destabilization of Soil Organic Carbon in Eroding and Depositional Settings, University of California, Berkley, 1-242 pp.

Berhe, A.A., Harden, J.W., Torn, M.S., Harte, J., 2008. Linking soil organic matter dynamics and erosion-induced terrestrial carbon sequestration at different landform positions. Journal of Geophysical Research 113, 1-12.

Bisigato, A.J., Laphitz, R.M.L., Carrera, A.L., 2008 Non-linear relationships between grazing pressure and conservation of soil resources in Patagonian Monte shrublands. . Journal of Arid Environments, 72, 1464–1475.

Bivand, R.S., Pebesma, E.J., Gómez-Rubio, V., 2008. Applied Spatial Data Analysis with R. Use R! Springer.

Bockheim, J.G., Birkeland, P.W., Bland, W.L. (Eds.), 2000. Carbon storage and accumulation rates in alpine soils: evidence from Holocene chronosequences. In Advances in Soil Science: Global Climate Change and Cold Ecosystems. CRC Press.

Bolin, B., Sukumar, R., 2000 Land Use, Land-use Change, and Forestry. In: R.T. Watson, I.R. Noble, B. Bolin, N.H. Ravindranath, D.J. Verardo, D.J. Dokken (Eds.), Special Report of the IPCC. Cambridge University Press, Cambridge, UK, pp. pp. 23–51.

Bolliger, J., Hagedorn, F., Leifeld, J., Böhl, J., Zimmermann, S., Soliva, R., Kienast, F., 2008. Potential effects of land-use change on carbon pools in Switzerland. Ecosystems 11, 895-907.

Bolstad, P.V., Vose, J.M., 2001. The Effects of Terrain Position and Elevation on Soil C in the Southern Appalachians. . In: LAL, R.; KIMBLE, J.M.; FOLLETT, R.F. & STEWART, B.A. (Ed.): Assessment methods for soil carbon. , Boca Raton (FL): Lewis Publishers, , p. 45-52.

Brady, N.C., Weil, R.R., 2002. The Nature and Properties of Soils., 13th edition, Prentice Hall.

Budge, K., Leifeld, J., Hiltbrunner, E., Fuhrer, J., 2011. Alpine grassland soils contain large proportion of labile carbon but indicate long turnover times. Biogeosciences, 8, 1911–1923.

Burke, I.C., E.T., E., C. V., C., 1995. Influence of Macroclimate, Landscape Position, and Mannagement on Soil Organic Matter in Agroecosystems Ecological Applications 5(1), 124-131.

Burke, I.C., Lauenroth, W.K., Riggle, R., Brannen, P., Madigan, B., Beard, S., 1999. Spatial Variability of Soil Properties in the Shortgrass Steppe: The Relative Importance of Topography, Grazing, Microsite, and Plant Species in Controlling Spatial Patterns. Ecosystems, 2, 422-438.

Burnham, J., Sletten, H., Sletten, R.S., 2010. Spatial distribution of soil organic carbon in northwest Greenland and underestimates of high Arctic carbon stores. Global Biogeochemical Cycles, 24, 1-14.

Campbell, J.E., Moen, J.C., Ney, R.A., Schnoor, J.L., 2008. Comparison of regression coefficient and GIS-based methodologies for regional estimates of forest soil carbon stocks. Environmental Pollution, 152 267-273.

Carter, M.R., Gregorich, E.G., 2006. Soil Sampling and Methods of Analysis, 2. CRC Press.

Catherine, P., Ouimet, R., 2008. Organic carbon, organic matter and bulk density relationships in boreal forest soils. Canadian Journal of Soil Sciences, 88, 315−325.

Cox, P.M., Betts, R.A., Jones, C.D., Spall, S.A., Totterdell, I.J., 2000. Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model. Nature, 408.

Czimczik, C., Mund, M., Schulze, E.D., Wirth, C., 2005. Effects of reforestation, deforestation, and afforestation on carbon storage in soils. Journal of Experimental Biology 319-330.

Dai, W., Huang, Y., 2006. Relation of soil organic matter concentration to climate and altitude in zonal soils of China. Catena 65, 87-94.

Dalal, R.C., Chan, K.Y., 2001. Soil organic matter in rainfed cropping systems of the Australian cereal belt. Australian Journal of Soil Research 39, 435–464.

Dawson, J.J., Smith, P., 2007. Carbon losses from soil and its consequences for land-use management. Science of the Total Environment 382, 165-190.

Dileep, K.P., Singh, R., Kundu, D.K., Chakraborty, H., Kumar, A., 2008. Improved estimation of soil organic carbon storage uncertainty using first-order Taylor series approximation. Soil Science Society of America Journal, 72, 1708–1710.

Djukic, I., Zehetner, F., Tatzber, M., Gerzabek, M.H., 2010. Soil organic-matter stocks and characteristics along an Alpine elevation gradient. Journal of Plant Nutrition and Soil Science 173, 30-38.

Don, A., Schumacher, J., Freibauer, A., 2011. Impact of tropical land-use change on soil organic carbon stocks – a meta-analysis. Global Change Biology, 17, 1658–1670.

Don, A., Schumacher, J., Scherer-Lorenzen, M., Scholten, T., Schulze, E.D., 2007. Spatial and vertical variation of soil carbon at two grassland sites – implications for measuring soil carbon stocks. Geoderma, 141( ), 272–282.

Egli, M., Sartori, G., Mirabella, A., Favilli, F., Giaccai, D., Delbos, E., 2009. Effect of north and south exposure on organic matter in high Alpine soils. Geoderma, 149, 124-136.

Eliseev, A.V., Mokhov, I.I., 2007. Carbon cycle–climate feedback sensitivity to parameter changes of a zero-dimensional terrestrial carbon cycle scheme in a climate model of intermediate complexity. Theoretical and Applied Climatology, 89, 9-24.

Ellert, B.H., Janzen, H.H., Entz, T., 2002. Assessment of a Method to Measure Temporal Change in Soil Carbon Storage. SSAJ, 66, 1687-1695.

Ellert, B.H., Janzen, H.H., Vandenbygaart, D.J., Bremer, E., 2008. Measuring Change in Soil Organic Carbon Storage. Soil Sampling and Methods of Analysis. 2nd Edition. Canadian Society of Soil Science. Taylor and Francis Group, Boca Raton (FL).

Falloon, P., Smith, P., 2009. Modelling soil carbon dynamics. Soil Carbon Dynamics. An Integrated Methodology. Cambridge University Press.

FAO (Ed.), 2004. Carbon Sequestration in dryland soil. World soil resources reports 102, Rome. (available at http://www.fao.org/docrep/007/y5738e/y5738e0d.htm.).

FAP, 1985. Eidgenössische Forschungsanstalt für landwirtschaftlichen Pflanzenbau: Bodenkarte Grindelwald mit Erläuterungen Bodenkarte der Schweiz 1:25 000. Bundesamt für Landestopographie, Zürich-Reckenholz.

Farage, P., Pretty, J., Ball, A., 2003. Biophysical Aspects of Carbon Sequestration in Drylands. Seminar paper presented at University of Essex, feb 03.

Franzluebbers, A.J., Stuedemann, J.A., Schomberg, H.H., Wilkinson, S.R., 2000. Soil organic C and N pools under long-term pasture management in the Southern Piedmont USA. Soil Biology & Biochemistry, 32 469–478.

Franzmeier, D.P., Lemme, G.D., Miles, R.J., 1985. Organic carbon in soils of north central United States. Soil Science Society of America Journal 49, 702–708.

Freibauer, A., Rounsevell, M., Smith, P., Verhagend, J., 2004. Carbon sequestration in the agricultural soils of Europe. Geoderma, 122(1), 1-23.

Friedlingstein, P., Cox, P., Betts, R., Bopp, L., Von Bloh, W., Brovkin, V., Cadule, P., Doney, S., Eby, M., Fung, I., Bala, G., John, J., Jones, C., Joos, F., Kato, T., Kawamiya, M., Knorr, W., Lindsay, K., Matthews, H.D., Raddatz, T., Rayner, P., Reick, C., Roeckner, E., Schnitzler, K.-G., Schnur, R., Strassmann, K., Weaver, A.J., Yoshikawa, C., Zeng, N., 2006. Climate–Carbon Cycle Feedback Analysis: Results from the C4MIP Model Intercomparison. Journal of Climate 19.

Fryer, G.I., Johnson, E.A., 1988. Reconstructing the fire behavior and effects in a subalpine forest. Journal of Applied Ecology 25, 1063-1072.

Ganuza, A., Gonzalo Almendros, 2003. Organic carbon storage in soils of the Basque Country (Spain): the effect of climate, vegetation type and edaphic variables. Biol Fertil Soils, 37, 154–162.

Garcia-Pausas, J., Casals, P., Camarero, L.s., Huguet, C., Sebastia`, M.-T., Thompson, J.A., Romanya`, J., 2007. Soil organic carbon storage in mountain grasslands of the Pyrenees: effects of climate and topography. Biogeochemistry, 82, 279–289.

Garcia-Pausas, J., Pere Casals, Lluı´s Camarero, Carme Huguet, Roy Thompson, Maria-Teresa Sebastia`, Joan Romanya`, 2008. Factors regulating carbon mineralization in the surface and subsurface soils of Pyrenean mountain grasslands. Soil Biology & Biochemistry, 40, 2803-2810.

Genxu, W., Ju, Q., Guodong, C., Yuanmin, L., 2002. Soil organic carbon pool of grassland soils on the Qinghai-Tibetan Plateau and its global implication. The Science of the total environment 291, 207-217.

Glenn, E., Squired, V., Olson, M., Frye, R., 1993. Potential for carbon sequestration in the drylands. Water, Air and Soil Pollution, 70, 341-355.

Gobin, A., Campling, P., Feyen, J., 2001. Soil-Landscape Modelling to Quantify Spatial Variability of Soil Texture. Physics and Chemistry of the earth, 26 (1), 41-45.

Goidts, E., van Wesemael, B., 2007. Regional assessment of soil organic carbon changes under agriculture in Southern Belgium (1955–2005). Geoderma, 141, 341-354.

Goidts, E., van Wesemael, B., Crucifix, M., 2009. Magnitude and sources of uncertainties in soil organic carbon (SOC) stock assessments at various scales. European Journal of Soil Science, 60, 723–739.

Greenlee, G.M., 1980. Soil Survey of designated areas within Kanaskis Provincial Park and interpretation for recreational use, Alberta Research Council Calgary Trail South. Edmonton, Alberta, pp. 68

Grigal, D.G., Ohmann, L.F., 1992. Carbon storage in upland forestland of the Lake States. Soil Science Society of America Journal, 56 935–943.

Grossmann, R.B., Harms, D.S., Kingsbury, D.F., Shaw, R.K., Jenkins, A.B., 2001 Assessment of Soil Organic Carbon Using the U.S. Soil Survey. Assessment methods for soil carbon. Lewis Publishers, Boca Raton (FL)

Grüneberg, E., Schöning, I., Kalko, E.K.V., Weisser, W.W., 2010. Regional organic carbon stock variability: A comparison between depth increments and soil horizons. Geoderma, 155, 426-433.

Guo, L.B., Gifford, R.M., 2002. Soil Carbon stocks and land use change: a meta analysis. Global Change Biology, 8, 345-360.

Haeberli, W., Keller, F., Krüsi, B., Egli, M., Rothenbühler, C., Meilwes, J., Gruber, S., 2007. GISALP. Raum-zeitliche Informationen über schnelle Klimaänderungen in hochalpinen Umweltsystemen als strategisches Werkzeug. , ETH Zürich.

Hancock, G.R., Murphy, D., Evans, K.G., 2010. Hillslope and catchment scale soil organic carbon concentration: An assessment of the role of geomorphology and soil erosion in an undisturbed environment. Geoderma, 155, 36-45.

Hartge, K.H., Horn, R., 2009. Die physikalische Untersuchung von Böden. Praxis Messmethoden Auswertung. Schweizerbart, Stuttgart.

Heckman, K., Welty-Bernard, A., Rasmussen, C., Schwartz, E., 2009. Geologic controls of soil organic cycling and microbial dynamics in temperate conifer forests. Chemical Geology 267, 12-23.

Hengl, T., Heuvelink, G.B.M., Alfred, S., 2004. A generic framework for spatial prediction of soil variables based on regression-kriging. Geoderma, 120, 75-93.

Hengl, T., Heuvelink, G.B.M., Rossiter, D.G., 2007. About regression-kriging: From equations to case studies. Computers & Geosciences 33, 1301-1315.

Hitz, C., 2002. Inventur und Dynamik der organischen Substanz in Böden der Alpinen Stufe. Untersuchungen im Vereina-Tal, GR, Schweiz. . Schriftenreihe Physische Geographie 42, Zürich.

Hitz, C., Egli, R., Fitze, P., 2001. Below-ground and above-ground production of vegetational organic matter along a climosequence in alpine grasslands. Journal of Plant Nutrition and Soil Science, 164 (4), 389-397.

Hoffmann, T., Glatzel, S., Dikau, R., 2009. A carbon storage perspective on alluvial sediment storage in the Rhine catchment. Geomorphology, 108, 127-137.

Hoffmann, U., Hoffmann, T., Johnson, E.A., Kuhn, J.N., submitted. Assessment of variability and uncertainty of soil organic carbon in a mountainous boreal forest (Canadian Rocky Mountains, Alberta). Geoderma.

Homann, P.S., Sollins, P., Chappell, H.N., Stangenberger, A.G., 1995. Soil Organic Carbon in a Mountainous, Forested Region: Relation to Site Characteristics. Soil Science Society of America Journal, 59, 1468-1475.

Houghton, R.A., 1995. Emissions of carbon from land-use change. The Carbon Cycle Cambridge University Press, Stanford.

Houghton, R.A., 2007. Balancing the Global Carbon Budget. Annual Review of Earth and Planetary Science, 35, 313-347.

IPCC, 2007. Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA.

Jackson, L.E., 1987. Terrain inventory of the Kananaskis Lakes Map Area, Alberta. Geological Survey of Canada, 86-12.

Jobbágy, E.G., Jackson, R.B., 2000. The vertical distribution of soil organic carbon and its relation to climate and vegetation. . Ecological Applications 10, 423-436.

Johnson, E.A., Larsen, C.P.S., 1991. Climatically Induced Change in Fire Frequency in the Southern Canadian Rockies. Ecology 72, 194–201.

Johnson, E.A., Wowchuk, D.R., 1993. Wildfires in the southern Canadian Rocky Mountains and their relationship to mid-tropospheric anomalies Canadian Journal of Forest Research, 23, 1213-1222.

Jones, C., McConnell, C., Coleman, K., Cox, P.M., Falloon, P., Jenkinson, D., Powlson, D., 2005. Global climate change and soil carbon stocks; predictions from two contrasting models for the turnover of organic carbon in soil. Global Change Biology, 11(1), 154-166.

Jones, R.J.A., Hiederer, R., Rusco, E., Loveland, P.J., Montanarella, L., 2004. The map of organic carbon in topsoils in Europe: VERSION 1.2 - SEPTEMBER 2003 Explanation of: Special Publication Ispra 2004 No.72 S.P .I.04.72, Luxembourg.

Kirschbaum, M.U.F., 2000. Will changes in soil organic carbon act as a positive or negative feedback on global warming? Biogeochemistry, 48, 21–51.

Kopacek, J., Kana, J., Santruckova, H., Picek, T., Stuchlik, E., 2004. Chemical and biochemical characteristics of alpine soils in the tatra mountains and their correlation with lake water quality. . Water, Air and Soil Pollution, 153, 307-327.

Körner, C., 2003. Alpine Plant Life: Functional Plant Ecology of High Mountain Ecosystems, Second Edition. Springer Berlin, Heidelberg, New York.

Krogh, L., Noergaard, A., Hermansen, M., Greve, M.H., Balstroem, T., Breuning-Madsen, H., 2003. Preliminary estimates of contemporary soil organic carbon stocks in Denmark using multiple datasets and four scaling-up methods. Agriculture, Ecosystems & Environment, 96(1), 19-28.

Kuhn, N.J., Hoffmann, T., Schwanghart, W., Dotterweich, M., 2009. Agricultural Soil Erosion and Global Carbon Cycle: Controversy over? . Earth Surface Processes and Landforms, 34, 1033-1038.

Kumar, S., Lal, R., 2011. Mapping the organic carbon stocks of surface soils using local spatial interpolator. Journal of Environmental Monitoring, 13, 3128-3135.

Kutsch, W.L., Bahn, M., Heinemeyer, A. (Eds.), 2009 Soil carbon relations: an overview Soil Carbon Dynamics. An Integrated Methodology. Cambridge University Press.

Labhart, T.P., 2005. Geologie der Schweiz, 7. Auflage. Ott Verlag, Bern.

Lacelle, B., Tarnocai, C., Waltman, S., Kimble, J., Orozco-Chaves, F., Jakobsen, B., 1997. Soil Organic Carbon Map of North America. In: USDA-NRCS/NSSC (Ed.), Lincoln, Nebraska.

Lal, R., 2003. Carbon Sequestration in Dryland Ecosystems. Environmental Management, 33(4), 528-544.

Lal, R., 2004. Soil Carbon Sequestration Impacts on Global Climate Change and Food Security. Science, 304, 1623-1627

Lal, R., 2005a. Forest soils and carbon sequestration. Forest Ecology and Management 220, 242-258.

Lal, R., 2005b. Soil erosion and Carbon dynamics. Soil and Tillage Research, 81(2), 137-142.

Lal, R., 2009. Sequestering Carbon in Soils of Arid Ecosystems. Land Degradation and Development, 20, 441-454.

Lal, R., Kimble, J.M., Stewart, B.A., 2011. Importance of soil bulk density and methods of its measurement. In : Assessment Methods for Soil Carbon. CRC Press.

Lark, R.M., 2005. Exploring scale-dependent correlation of soil properties by nested sampling. European Journal of Soil Science, 56, 307-317.

Leifeld, J., Bassin, S., Fuhrer, J., 2005. Carbon stocks in Swiss agricultural soils predicted by land-use, soil characteristics, and altitude. Agriculture, Ecosystems and Environment 105, 255-266.

Leifeld, J., Fuhrer, J., 2009. Long-term management effects on soil organic matter in two cold, high-elevation grasslands: clues from fractionation and radiocarbon dating. European Journal of Soil Science, 60, 230-239.

Leifeld, J., Zimmermann, M., Fuhrer, J., Conen, F., 2009. Storage and turnover of carbon in grassland soils along an elevation gradient in the Swiss Alps. Global Change Biology, 15, 668-679.

Leopold, U., Heuvelink, G.B.M., Tiktak, A., Finke, P.A., Schoumans, O., 2006. Accounting for change of support in spatial accuracy assessment of modelled soil mineral phosphorous concentration. Geoderma, 130, 368-386.

Li, J., Heap, A.D., 2011. A review of comparative studies of spatial interpolation methods in environmental sciences: Performance and impact factors. Ecological Informatics, 6, 228-241.

Lieb, G., Kellerer-Pirklbauer-Eulenstein, A., Strasser, U. (Eds.), 2011. Effekte des Klimawandels im Naturraum des Hochgebirges Geographie für eine Welt im Wandel: Umwelt - Gesellschaft - Geokommunikation. Vienna University Press.

Liechty, H.O., Jurgensen, M.F., Mroz, G.D., Gale, M.R., 1997. Pit and mound topography and its influence on storage of carbon, nitrogen, and organic matter within an old-growth forest. Can. J. For. Res., 27.

Lo, E., 2005. Gaussian Error Propagation applied to ecological data: Post-ice-storm-downed woody biomass Ecological Monographs, 75(4).

Lopez-Granados, F., Jurado-Exposito, M., Pena-Barragan, J., Garcia-Torres, L., 2005. Using geostatistical and remote sensing approaches for mapping soil properties. European Journal Agronomy, 23((33)), 279-289.

Luyssaert, S., Schulze, E.-D., Börner, A., Knohl, A., Hessenmöller, D., Law, B.E., Ciais, P., Grace, J., 2008. Old-growth forests as global carbon sinks. Nature, 455, 213-215.

Mabit, L., Bernard, C., Makhlouf, M., Laverdiere, M.R., 2008. Spatial variability of erosion and soil organic matter content estimated from 137Cs measurements and geostatistics. Geoderma, 145(3-4), 245-251.

Macias, F.M., Johnson, E.A., 2006. Large-scale climatic patterns control large lightning fire occurrence in Canada and Alaska forest regions. Journal of Geophysical Research, 111(G04008. DOI: 10.1029/2006JG000181).

Manley, J.T., Schuman, G.E., Reeder, J.D., Hart, R.H., 1995. Rangeland soil carbon and nitrogen responses to grazing. Journal of Soil & Water Conservation, 50, 294–298.

Martin, M.P., M. Wattenbach, P. Smith, J. Meersmans, C. Jolivet, L. Boulonne and D. Arrouays, 2011. Spatial distribution of soil organic carbon stocks in France. Biogeosciences, 8, 1053-1065.

Mayorga, E.A.K.A., C.A. Masiello, A.V. Krusche, J.I. Hedges, P.D. Quay, J.E. Richey and T.A. Brown, 2005. Young organic matter as a source of carbon dioxide outgassing from Amazonian rivers. Nature, 436, 538-541.

McGregor, C.A., 1984. Ecological Land Classification and Evaluation. Kananaskis Country Volume I Natural Resource Summary. Edmonton: Alberta Energy and Natural Resources.

Meehl, G.A., Stocker, T.F., Collins, W.D., Friedlingstein, P., Gaye, A.T., Gregory, J.M., Kitoh, A., Knutti, R., Murphy, J.M., Noda, A., Raper, S.C.B., Watterson, I.G., Weaver, A.J., Z.-C. Zhao (Eds.), 2007. Global Climate Projections. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. In: Climate Change 2007: The Physical Science Basis. . Cambridge University Press,.

Meersmans, J., Ridder, F.D., Canters, F., Baets, S.D., Molle, M.V., 2008. A multiple regression approach to assess the spatial distribution of Soil Organic Carbon (SOC) at the regional scale (Flanders, Belgium). Geoderma, 143, 1-13.

Meersmans, J., Wesemael, B.v., Ridder, F.D., Molle, M.V., 2009. Modelling the three-dimensional spatial distribution of soil organic carbon (SOC) at the regional scale (Flanders, Belgium). Geoderma, 152, 43-52.

Mishra, U., 2009. Predicting storage and dynamics of soil organic carbon at a regional scale. Dissertation.

Mishra, U., Lal, R., Slater, B.K., Calhoun, F., Liu, D., Van Meirvenne, M., 2009. Predicting Soil Organic Carbon Stock Using Profile Depth Distribution Functions and Ordinary Kriging. Soil Science Society of America Journal, 73(2), 614-621.

Moelders, N., Jankov, M., Kramm, G., 2005. Application of Gaussian Error Propagation Principles for Theoretical Assessment of Model Uncertainty in Simulated Soil Processes Caused by Thermal and Hydraulic Parameters. American Meteorological Society, 6, 1045-1062.

Moni, C., Chabbi, A., Nunan, N., Rumpel, C., Chenu, C., 2010. Spatial dependance of organic carbon–metal relationships A multi-scale statistical analysis, from horizon to field. Geoderma, 158, 120-127.

Montgomery, D.R., 2007. Is agriculture eroding civilization´s foundation? . GSA Today, 17(19), 4-9.

Moorman, T.B., Cambardella, C.A., James, D.E., Karlen, D.L., Kramer, L.A., 2004. Quantification of tillage and landscape effects on soil carbon in small Iowa watersheds. Soil & Tillage Research, 78, 225–236.

Morgan, J.A., Follett, R.F., Allen, L.H.J., Del Grosso, S., Derner, J.D., Dijkstra, F., Franzluebbers, A., Fry, R., Paustian, K., Schoeneberger, M.M., 2010. Carbon sequestration in agricultural lands of the United States. Journal of soil and water conservation, 65(1), 6A-13A.

Olsvig-Whittaker, L., Shachak, M., Yair, A., 1983. Vegetation patterns related to environmental factors in a Negev Desert watershed. Vegetation, 54(3), 153-165.

Pennock, D.J., van Kessel, C., 1997. Effect of agriculture and of clear-cut forest harvest on landscape-scale soil organic carbon storage in Saskatchewan. CANADIAN JOURNAL OF SOIL SCIENCE, 77(2), 211-218.

Perruchoud, D., Kienast, F., Kaufmann, E., Braker, O.U., 1999. 20th Century Carbon Budget of Forest Soils in the Alps. Ecosystems 2, 320-337.

Perruchoud, D., Walthert, L., Zimmermann, S., Lüscher, P., 2000. Contemporary carbon stocks of mineral forest soils in the Swiss Alps. Biogeochemistry, 50, 111-136.

Phachomphon, K., Dlamini, P., Chaplot, V., 2010. Estimating carbon stocks at a regional level using soil information and easily accessible auxiliary variables. Geoderma, 155, 372-380.

Ping, C.-L., Michaelson, G.J., Jorgenson, M.T., Kimble, J.M., Epstein, H., Romanovsky, V.E., Walker, D.A., 2008. High stocks of soil organic carbon in the North American Arctic region. Nature Geoscience, 1, 615-619.

Poeplau, C., Axel Don, Lars Vesterdal, Jens Leifeld, Bas van Wesemael, Schumacher, J., Gensior, A., 2011. Temporal dynamics of soil organic carbon after land-use change in the temperate zone – carbon response functions as a model approach. Global Change Biology, 17, 2415–2427.

Post, W.M., Kwon, K.C., 2000. Soil Carbon Sequestration and Land-Use Change: Processes and Potential. Change Biology 6, 317-328.

Pregitzer, K.S., Euskirchen, E.S., 2004. Carbon cycling and storage in world forests: biome patterns related to forest age. Global Change Biology 2004/10, 2052-2077.

Price, M.V., Waser, N.M., 2000. Responses of subalpine meadow vegetation to four years of experimental warming. Ecological Applications, 10, 811-823.

Prichard, S.J., Peterson, D.L., Hammer, R.D., 2000. Carbon Distribution in Subalpine Forests and Meadows of the Olympic Mountains, Washington. Soil Sci. Soc. Am. J., 64, 1834-1845.

Quine, T.A., Oost, K.v., 2007. Quantifying carbon sequestration as a result of soil erosion and deposition: retrospective assessment using caesium-137 and carbon inventories. Global Change Biology, 13, 1-16.

Quinton, J.N., Govers, G., Van Oost, K., Bardgett, R.D., 2010. The impact of agricultural soil erosion on biogeochemical cycling. Nature Geoscience, 3, 311-314.

Ravindranath, N.H., Ostwald, M., 2008. Carbon Inventory Methods. Handbook for greenhouse gas inventory, Carbon mitigation and roundwood production projects. Advances in global change research (29). Springer Science + Business Media B.V.

RC612, 2006. Instruction Manual RC612, Multiphase Carbon/Hydrogen/Moisture Determinator. Version 1.0 Leco Corporation. .

Riedo, M., Gyalistras, D., Fuhrer, J., 2001. Pasture responses to elevated temperature and doubled CO2 concentration: assessing the spatial pattern across an alpine landscape. Climate Research 17, 19-31.

Rodeghiero, M., Heinemeyer, A., Schrumpf, M., Bellamy, P., 2009. Determination of soil carbon stocks and changes. In: W.L.B. Kutsch, M. & Heinemeyer, A. (Ed.) (Ed.), Soil Carbon Dynamics. An Integrated Methodology. Cambridge University Press, New York, pp. 49-75.

Rotenberg, E., Yakir, D., 2010. Contribution of Semi-Arid Forests to the Climate System. Science, 327, 451.

Schawe, M., Glatzel, S., Gerold, G., 2007. Soil development along an altitudinal transect in a Bolivian tropical montane rainforest: Podzolization vs. hydromorphy. Catena, 69, 83-90.

Schimel, D., Melillo, J., Tian, H., 2000. Contribution of increasing CO2 and climate to carbon storage by ecosystems in the United states. Science, 287, 2004-2006

Schlesinger, W.H., 1990. Evidence from chronosequence studies for a low carbon-storage potential of soils. Nature 348, 232-234.

Schlesinger, W.H., 1995. An Overview of the carbon cycle. In: R.K. Lal, J.; Levine, E. & Stewart, B. A. (Ed.) (Ed.), Soils and Global Change. Lewis Publishers, pp. 9-26.

Schlesinger, W.H., J., P.W., Megonigal, P.J., 2000. Soils and the Global Carbon Cycle. In: T.M.L.S. Wigley, D. S. (Ed.) (Ed.), The Carbon Cycle. Cambridge University Press, New York.

Schlünz, B., Schneider, R.R., 2000. Transport of terrestrial organic carbon to the oceans by rivers: re-estimating flux- and burial rates. International Journal of Earth Sciences 88, 599-606.

Schnabel, R.R., Franzluebbers, A.J., Stout, W.L., Sanderson, M.A., Stuedemann, J.A., 2001. The effects of pasture management practices In: J.M.K.a.R.L. Eds R. F. Follet (Ed.), In 'Potential of US Grazing Lands to Sequester Carbon and Mitigate the Greenhouse Effect' CRC Press LLC: USA.

Schröter, D., Cramer, W., Leemans, R., Prentice, I.C., Araújo, M.B., Arnell, N.W., Bondeau, A., Bugmann, H., Carter, T.R., Gracia, C.A., De La Vega-Leinert, A.C., Erhard, M., Ewert, F., Glendining, M., House, J.I., Kankaanpää, S., Klein, R.J.T., Lavorel, S., Lindner, M., Metzger, M.J., Meyer, J., Mitchell, T.D., Reginster, I., Rounsevell, M., Sabaté, S., Sitch, S., Smith, B., Smith, J., Smith, P., Sykes, M.T., Thonicke, K., Thuiller, W., Tuck, G., Zaehle, S., Zierl, B., 2005. Ecosystem service supply and vulnerability to global change in Europe. Science, 310, 1333–1337.

Schrumpf, M., Schulze, E.D., Kaiser, K., Schumacher, J., 2011. How accurately can soil organic carbon stocks and stock changes be quantified by soil inventories? Biogeosciences, 8, 723–769.

Schuman, G.E., Herrick, J.E., Janzen, H.H., 2001. The dynamics of soil carbon in rangelands. In: The Potential of U.S. Grazing Lands to Sequester Carbon and Mitigate the Greenhouse Effect (eds R.F. Follett, J.M. Kimble & R. Lal), Lewis Publishers, Boca Raton, FL., pp. 267–290.

Schwager, S.J., Mikhailova, E.A., 2002. Estimating variability in soil organic carbon storage using the methods of statistical differentials. Soil Science, 167(3), 194-200.

Schwanghart, W., Jarmer, T., 2011. Linking spatial patterns of soil organic carbon to topography — A case study from south-eastern Spain. Geomorphology, 126, 252-263.

Sedjo, R.A., 1992. Temperate Forest Ecosystems in the Global Carbon Cycle. Ambio, 21, 274-277.

Seeber, J., G.U.H. Seeber, 2005. Effects of land-use changes on humus forms on alpine pastureland (Central Alps, Tyrol). Geoderma, 124, 215–222.

Sheikh, M.A., Kumar, M., Bussmann, R.W., 2009. Altitudinal variation in soil organic carbon stock in coniferous subtropical and broadleaf temperate forests in Garhwal Himalaya. Carbon Balance and Management, 4(6).

Shukla, M.K., Lal, R., 2005. Erosional effects on soil organic carbon stock in an on-farm study on Alfisols in west central Ohio. Soil & Tillage Research, 81, 171-181.

Simbahan, G.C., Dobermann, A., 2006. Sampling optimization based on secondary information and its utilization in soil carbon mapping. Geoderma, 133, 345-362.

Simbahan, G.C., Dobermann, A., Goovaerts, P., Ping, J., Haddix, M.L., 2006. Fine-resolution mapping of soil organic carbon based on multivariate secondary data. Geoderma, 132, 471-489.

Simó, I., Herrero, C., Boixadera, J., Poch, R.M., 2010. Accuracy of soil organic carbon inventories in Mediterranean mountain areas. World Congress of Soil Science.

Singh, S.K., Pandey, C.B., Sidhu, G.S., Sarkar, D., Sagar, R., 2011. Concentration and stock of carbon in the soils affected by land uses and climates in the western Himalaya, India. Catena, 87, 78-89.

Slaymaker, O., Spencer, T., Embleton-Hamann, C., 2009. Geomorphology and global environmental change, Cambridge University Press.

Smith, J.E., Heath, L.S., 2000. Consideration for interpreting probalistic estimates of uncertainty of forest carbon USDA, 102-111.

Smith, P., 2004a. Carbon sequestration in croplands: the potential in Europe and the global context. European Journal Agronomy, 20, 229-236.

Smith, P., 2004b. Soils as carbon sinks: the global context. Soil Use and Management, 20, 212-218.

Spielvogel, S., Jörg, P., Auerswald, K., Kögel-Knabner, I., 2009. Site-specific spatial patterns of soil organic carbon stocks in different landscape units of a high-elevation forest including a site with forest dieback. Geoderma, 152, 218-230.

Stallard, R.F., 1998. Terrestrial sedimentation and the carbon cycle: Coupling weathering and erosion to carbon burial. Global Biogeochemical Cycles, 12, 231-257.

Stutter, M.I., Lumsdon, D.G., Billett, M.F., Low, D., Deeks, L.K., 2009. Spatial Variability in Properties Affecting Organic Horizon Carbon Storage in Upland Soils. Soil Science Society of America Journal, 73, 1724-1732.

Tan, Z.X., Lal, R., Smeck, N.E., Calhoun, F.G., 2004. Relationships between surface organic carbon pool and site variables. Geoderma, 121, 187-195.

Taylor, J.R., 1997. An Introduction to Error Analysis. The Study of Uncertainties in Physical Measurements. University Science Books, Sausalito.

Theurillat, J.-P., Felber, F., Geissler, P., Gobat, J.-M., Fierz, M., Fischlin, A., Küpfer, P., Schlüssel, A., Velluti, C., Zhao, G.-F., Williams, J., 1998. Sensitivity of Plant and Soil Ecosystems of the Alps to Climate Change. . In: P.D. Cebon, U.; Davies, H. C.; Imboden, D. & Jaeger, C. C. (Ed.) (Ed.), Views from the Alps. Regional Perspectives on Climate Change. MIT Press., Massachusetts:.

Theurillat, J.-P., Guisan, A., 2001. Potential impact of climate change on vegetation in the European alps: a review. Climatic Change, 50, 77–109.

Van Miegroet, H., Boettinger, J.L., Baker, M.A., Nielsen, J., Evans, D., Stum, A., 2005. Soil carbon distribution and quality in a montane rangeland-forest mosaic in northern Utah. Forest Ecology and Management, 220, 284-299.

Van Miegroet, H., Moore, P.T., Tewksbury, C.E., Nicholas, N.S., 2007. Carbon sources and sinks in high-elevation spruce–fir forests of the Southeastern US. Forest Ecology and Management, 238, 249-260.

Van Oost, K., Quine, T.A., Govers, G., De Gryze, S., Six, J., Harden, J.W., Ritchie, J.C., McCarty, G.W., Heckrath, G., Kosmas, C., Giraldez, J.V., Marques da Silva, J.R., Merckx, R. , 2007. The impact of agricultural soil erosion on the global carbon cycle. Science, 318, 626-629.

van Wesemael, B., Paustian, K., Meersmans, J., Goidts, E., Barancikova, G., Easter, M., 2010. Agricultural management explains historic changes in regional soil carbon stocks. Proceedings of the National Academy of Sciences, 107(33), 14926–14930.

Vardy, S.R., Warner, B.G., Turunen, J., Aravena, R., 2000. Carbon accumulation in permafrost peatlands in the Northwest Territories and Nunavut, Canada. The Holocene, 10(2), 273-280.

Vogt, K.A., Grier, C.C., Vogt, D.J., 1986. Production, turnover, and nutrient dynamics of above- and belowground detritus of world forests. Advances in Ecological Research 15, 303–377.

Vogt, K.A., Vogt, D.J., Brown, S., Tilley, J.P., Edmonds, R.L., Silver, W.L., Siccama, T.G. (Eds.), 1995. Dynamics of forest floor and soil organic matter accumulation in boreal,

temperate, and tropical forests. . Soils and the green- house effect John Wiley & Sons.
Wang, D.D., Shi, X.-Z., Wang, H.-J., D. C., W., Yu, D.-S., Sun, W.-X., Ren, H.-Y., Zhao, Y.-C., 2010. Scale Effect of Climate and Soil Texture on Soil Organic Carbon in the Uplands of Northeast China. Pedosphere, 20(4), 525-535.
Wang, S., Huang, M., Shao, X., Mickler, R.A., Li, K., Ji, J., 2004. Vertical Distribution of Soil Organic Carbon in China. Environmental Management, 33(1), 200-209.
Wang, Z.M., Zhang, B., Song, K.S., Liu, D.W., Li, F., Guo, Z.X., Zhang, S.M., 2008. Soil organic carbon under different landscape attributes in croplands of Northeast China. Plant Soil Environ. , 54, 420-427.
Wigley, T.M.L., Schimel, D.F. (Eds.), 2005. The Carbon Cycle. Cambridge University Press.
Williams, J.A., 1990. Part I: Vegetation Inventory of the Kananaskis, Opal and Misty Ranges in Peter Lougheed Provincial Park. . In: Vegetation of Peter Lougheed Provinvial Park. Canmore (AB): Alberta Recreation and Parks, Kananaskis Country Operations Branch, Environmental Management. .
Wu, H., Zhengtang, G., Changhui, P., 2003. Distribution and storage of soil organic carbon in China. Global Biogeochemical Cycles, 17(2).
Wüthrich, C.L., H. , 2004. Geoökologischer Laborkurs - „Das Handbuch zum Kurs“. Version 2004. Geographisches Institut der Universität Basel: Physiogeographie und Landschaftsökologie.
Xianli, X., Liu, W., Kiely, G., 2010. Modeling the change in soil organic carbon of grassland in response to climate change: Effects of measured versus modelled carbon pools for initializing the Rothamsted Carbon model. Agriculture, Ecosystems & Environment.
Yair, A., 1990. The role of topography and surface cover upon soil formation along hillslopes in arid climates. Geomorphology, 3, 287-299.
Yair, A., 1994. The ambiguous impact of climate change at a desert fringe: Northern Negev, Israel, A.C In: K.P. A.C. Millington (Ed.), Environmental Change in Drylands: Biogeographical and Geomorphological Perspectives. Wiley, Chichester, UK pp. pp. 199–227.
Yair, A., Danin, A., 1980. Spatial variations in vegetation as related to the soil moisture regime over an arid limestone hillside, Northern Negev Israel. Oecologia, 47, 83-88.
Yang, Y., Fang, J., Tang, Y., Ji, C., Zheng, C., He, J., Zhu, B., 2008. Storage, patterns and controls of soil organic carbon in the Tibetan grasslands. Global Change Biology, 14, 1592–1599.
Yemefack, M., Rossiter, D.G., Njomgang, R., 2005. Multi-scale characterization of soil variability within an agricultural landscape mosaic system in southern Cameroon. Geoderma, 125, 117–143.
Yoo, K., Amundson, R., Heimsath, A.M., Dietrich, W.E., 2005. Erosion of upland hillslope soil organic carbon: Coupling field measurements with a sediment transport model. Global Biogeochemical Cycles, 19, 1-17.
Yoo, K., Amundson, R., Heimsath, A.M., Dietrich, W.E., 2006. Spatial patterns of soil organic carbon on hillslopes: Integrating geomorphic processes and the biological C cycle. Geoderma, 130, 47-65.
Zeller, V., Bahn, M., Aichner, M., Tappeiner, U., 2000. Impact of land-use change on nitrogen mineralization in subalpine grasslands in the southern Alps. . Biology & Fertility of Soils, 31, 441–448.
Zeller, V., Kandeler, E., Mair, V., 1997. N dynamic in mountain grassland with different intensity of cultivation. . Bodenkultur, 48, 225–238.

Zeng, N., Qian, H., Munoz, E., Iacono, R., 2004. How strong is carbon cycle-climate feedback under global warming? Geophysical Research Letters 31.

Zhang, C., 2007. Fundamentals of Environmental Sampling and Analysis. John Wiley & Sons, Inc.

Zhang, C., McGrath, D., 2004. Geostatistical and GIS analyses on soil organic carbon concentrations in grassland of southeastern Ireland from two different periods. Geoderma, 119, 261-275.

Zhao, Y., Shi, X., Yu, D., Wang, H., Sun, W., 2005. Uncertainty assessment of spatial patterns of soil organic carbon density using sequential indicator simulation, a case study of Hebei province, China. Chemosphere, 59, 1527-1535.

Zhen, T., Chengde, S., Quanzhou, G., Yanmin, S., Weixi, Y., Yingnian, L., 2007. Soil organic carbon storage and soil CO2 flux in the alpine meadow ecosystem. Science in China Series D: Earth Sciences 50(7), 1103-1114.

Zhou, G., Liu, S., Li, Z., Zhang, D., Tang, X., Zhou, C., Yan, J., Mo, J., 2006. Old-Growth Forests can accumulate Carbon in Soils. Science, 314, 1417.

Acknowledgements

I am deeply thankful to many people that helped, inspired and encouraged me to progress and complete this dissertation. First and foremost, I thank Prof. Dr. Nikolaus Josef Kuhn, my doctoral supervisor, who always supported me in every possible way. I am very grateful for his inspiration and scientific advice, his patience in answering all my questions and his constructive criticism. I also extend sincere thanks to Prof. Dr. Stephan Glatzel for his willingness to supervise my work, for his time and support, his interest and for his feedback and successful discussions.

Many other people contributed to make my time at the Department of Environmental Science productive and pleasurable. I want to thank my colleagues and friends who supported me during my field-work. I never want to miss the great time we had. I am very grateful to my colleagues and friends at the University of Basel Edith Beising, Rosi Gisin, Wolfgang Schwanghart, Harald Hikel, Sarah Strähl, Matthias Hunziker, Chatrina Caviezel, Lena Bloemertz and Wolfgang Fister. Your fruitful discussions, support and friendship created a motivating and fun working environment. Many students contributed to making these investigations possible. I want to thank Michelle Marbach, Stefanie Lauber, Dominik Mösch, Martin Classen and Kathrin Naegeli for field and lab-assistance.

I am very thankful to Heidi Strohm, Marianne Caroni, Ruth Strunk and Hans-Rudolf Rüegg for technical support and for the patience they had with all the chaos I produced in the lab.

I thank my parents, my brother and my sister and Thommes for their support and encourage in every way before and during my PhD. I cannot thank you enough for your love and care.

My PhD work was financially supported by the Swiss Academy of Science and the Freie Akademische Gesellschaft. I am very thankful for the Doctoral Student Research Award by the "Department of Foreign Affairs and International Trade Canada", which financially supported the field-work in Kananaskis, (AB, Canada). Furthermore I thank Ed Johnson and the Biogeoscience Institute of the University of Calgary for logistic and lab support at the Barrier Lake field station, Kananaskis.